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Shrinking training budgets pose a serious problem to those confronted with the present and future challenge of providing competent Air Force technicians for increasingly technical positions in a modern Air Force. One promising solution to this problem has been to harness the capabilities of the computer as an instructional training device. To be cost-effective, computer-based instruction must maximize individual student attainment of training objectives, while simultaneously minimizing training time and costs. Adaptive Instructional Models (AIM) constitute the means by which effective training can be accomplished with a minimum expenditure of student time and instructional resources. The report describes the purpose and function of AIM. Additionally, seven adaptive instructional models are analyzed, and recommendations as to model application in Air Force technical training courses are made. (Author)

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THE ANALYSIS AND DEVELOPMENT OF AN ADAPTIVE INSTRUCTIONAL MODEL(S) FOR INDIVIDUALIZED TECHNICAL TRAINING – PHASE I

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August 1973

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13. ABSTRACT

Shrinking training budgets pose a serious problem to those confronted with the present and future challenge of providing competent Air Force technicians for increasingly technical positions in a modern Air Force. One promising solution to this problem has been to harness the capabilities of the computer as an instructional training device. To be cost-effective, computer-based instruction must maximize individual student attainment of training objectives, while simultaneously minimizing training time and costs. Adaptive Instructional Models (AIM) constitute the means by which effective training can be accomplished with a minimum expenditure of student time and instructional resources. The report describes the purpose and function of AIM. Additionally, seven adaptive instructional models, to include supporting literature, have been analyzed and recommendations as to model application in Air Force technical training courses have been made.

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SUMMARY

Problem

Objectives of the Phase I research were to (1) provide in a single source, a comprehensive review and anlysis of state-of-the-art developments in adaptive instructional models and (2) recommend which adaptive instructional models as a subsystem of the Advanced Instructional System (AIS) were suitable for implementation within three Air Force technical training courses (Precision Measuring Equipment, Inventory Management, and Weapons Mechanic).

Approach

Literature searches were conducted to identify and document current trends in both the research and development of adaptive instructional models. Professional contacts and surveys of facilities currently exercising computer-managed adaptive instructional models were made. Based upon these information sources and familiarity with student characteristics associated with the three designated Air Force technical courses, specific recommendations were made for optimizing, incorporating, and implementing instructional models within the AIS.

Results

Five Adaptive Instructional Models (AIM) useful for specific instructional tasks were recommended for immediate implementation within the AIS. Briefly, the five adaptive models and their associated tasks were (1) *Drill-and-Practice*–increases student proficiency and speed; (2) *Concept Acquisition*–facilitates concept attainment by varying the sequence, amount, and kind of examples; (3) *Complex Tutorial*–provides the student with strategies with which to master rule-learning and problem-solving; (4) *Algorithmic Regression*–details a plan of instruction for each student in the form of a prescription, assigns resources, provides incentives, and monitors outcomes for input into the next individualized prescription; (5) *Dynamic Programming*– a master instructional model which is capable of incorporating previously mentioned models in order to optimize student progress, proficiency, and instructional resources.

Two additional models were analyzed and recommended for further research prior to field implementation within the AIS. These models include (1) Natural Language Processing and (2) Automaton Models.

Conclusions

Five state-of-the-art Adaptive Instructional Models were recommended for inclusion within the AIS. A future technical report (Phases II & III) shall report: (1) findings of computer simulations of three of these models, and (2) a step-by-step guide to how these models may be used to maximize student performance while minimizing student training time and instructional resources expended.

PREFACE

This report documents a comprehensive analysis of state-of-the-art developments in adaptive instructional models. Recommendations as to the suitability of numerous instructional models for application in Air Force training have been provided.

Research was accomplished in support of Project 1193, Advanced Instructional System (AIS), Task 0B05, Analysis and Development of Adaptive Instructional Models for Individualized Technical Training. Mr. Joseph Yasutake was the Project Scientist, and Dr. Gerard M. Deignan was the Task Scientist.

Research contained herein was conducted under the provisions of Contract F33615-72-C-1277 by Dr. Duncan N. Hansen and his staff at the Center for Computer Assisted Instruction, Florida State University. Subsequent technical reports under this contract shall provide computer simulations of three adaptive instructional models and their technical training applications in Air Force settings.

Grateful appreciation is extended to two individuals for their personal contributions during the course of this research. Dr. Marty Rockway, Technical Director, made sound scientific suggestions in several portions of the manuscript. As evidenced by the original statement of work, Dr. Pat-Anthony Federico provided the research impetus and initial technical monitorship in the formative research stages of this contract. The summary and overview was prepared by Dr. Gerard M. Deignan, Technical Training Division, Air Force Human Resources Laboratory.

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THE ANALYSIS AND DEVELOPMENT OF AN ADAPTIVE INSTRUCTIONAL MODEL(S) FOR INDIVIDUALIZED TECHNICAL TRAINING–PHASE I

I. THE NATURE AND ROLE OF ADAPTIVE INSTRUCTIONAL MODELS

Overview

Adaptive Instructional Models (AIM) provide the means by which instructional task factors, materials, and resources are continuously tailored or adapted to match the changing instructional needs, skills, and interest motivations of individual students–and seeks to do so in a cost-effective manner. Indeed, providing more cost-effective training by maximizing individual student attainment of training objectives, while simultaneously minimizing the completion time and costs of such training, is the primary concern of this project.

To provide a more meaningful context for discussing the AIM, it might be helpful to describe, briefly, the larger Advanced Instructional System (AIS) within which the AIM subsystem is embedded.

The AIS is a prototype, computer-based, individualized training system and research facility designed to improve and maintain the cost-effectiveness of technical training. Individualization of technical instruction, computer management of instructional resources, and evaluation of instructional strategies are some of the AIS provisions anticipated to contribute considerably to the effectiveness and efficiency of technical training. Additionally, to exploit the utility of future instructional innovations, the AIS will serve as an evaluative testbed for promising instructional technology.

Initially, the AIS shall be implemented in three Air Force technical courses: (1) Precision Measuring Equipment, (2) Weapons Mechanic, and (3) Inventory Management. At the conclusion of this stage, the AIS shall operate as a totally integrated computer-based system, capable of training approximately 2,100 students in the three courses with a 25-percent average reduction in training time. Furthermore, time savings shall be accompanied by training proficiency equal to or better than former, non-AIS graduates.

For the purpose of discussion, the AIS might be compared to the structures and resources of the human body, wherein the AIM's constitute the integrated "brain" of the AIS. This particular brain assimilates and stores information about each individual student's characteristics, and it compares such information to current instructional tasks. Based upon this stored information, the brain scans the available instructional material, media, and other resources to determine the level of content to present and the best method of presenting it. The brain then composes a strategy which attempts to maximize student performance with a minimum expenditure of student time and instructional resources.

Because this brain continuously monitors and manages not only student performance, but instructional resources availability as well, it is capable of learning more about each student, to include which instructional methods, materials, media, and incentives are performance effective. Hence, instructional strategy effectiveness becomes progressively more accurate. Furthermore, if certain instructional equipment is predicted to be in short supply at a particular point in time, the brain may prescribe an alternate instructional path which permits equipment use at a more appropriate time. Adaptability to constraints of limited instructional resources and the proper scheduling of resources are major determining conditions of instructional strategy effectiveness and related time savings.

The objectives of the AIM's contribute directly to the goals of AIS, namely, individualization of the training process, computer-management of resources, use of cost-effective multimedia approaches, and training systems modularity. Specifically, AIM contributes to the following AIS goals:

- *Adaptiveness*– AIM provides for individualization of the training process based on student characteristics and specific training strategies.
- *Flexibility*– AIM provides training alternatives in content, media, and personnel assignements.
- *Expandability*– AIM provides an updating mechanism by which more proficient instruction can occur.
- *Modularity*– AIM provides alternative models which can be utilized according to the appropriate match between training task requirements and specific individual differences.

- *Cost Effectiveness* – AIM attempts to optimize student motivation with incentive schemes that will lead to significant reductions in training time.

The objectives of AIM can be stated as follows:

- To provide a fine-grained monitoring of each student's performance
- To provide a set of training decision rules that optimize students' motivation and progress
- To provide a decision-allocation procedure that optimally assigns instructional media, material, and incentive rewards according to each student's characteristics and performance
- To provide predictions of performance and time parameters for each student
- To provide for the scheduling of all instructional resources so as to minimize cost.

An extensive review of prior research and theoretical literature has led to an initial classification of the adaptive models into seven groups. As is described in this report, five of these model groups are recommended for immediate implementation within AIS. The remaining two model groups, being more abstract, are recommended for additional research investigation prior to incorporation within the AIS program. The essential features of all seven adaptive models are discussed in the following paragraphs.

The first model, *Drill-and-Practice*, has two primary goals, namely, (1) to improve the student's accuracy, and (2) to increase his speed of performance. Drill-and-practice models primarily provide for appropriate problem selection and control of instructional presentation and/or student response rates so as to achieve their overall goal. The drill-and-practice models will typically be embedded in strategies for practice following demonstration, remediation, and review. These practice strategies are especially important in technical training environments. From an operational point of view, the drill-and-practice model provides for a computer-based composition of a set of problems, appropriately graded and ordered as to difficulty. To a large extent, attainment of specified criterion levels of skill performance depends upon proper sequences and amounts of practice and review.

Concept Acquisition Models provide for the dynamic manipulation of factors related to pretask and within-task variables so as to facilitate learning processses. Pretask variables concern prior knowledge, ability, and learning styles which are used to manipulate both the concept-content and content-difficulty levels. Within-task variables provide for a systematic manipulation of positive and negative examples, the number of examples, the degree of prompting, and the nature of the correctional feedback process. Thus the concept acquisition models provide for extensive adaptability appropriate to the diversity of technical concepts found within AIS.

Complex Tutorial Models provide the strategies by which rule-learning and problem-solving behaviors can be achieved by students. The complex tutorial model utilizes a combination of multiple regression techniques and explicit decision rules to select instructional content, examples, and problems to compose individualized lesson sequences for a given student. The decision rules will relate such task characteristics as rule difficulty, problem difficulty, and/or example difficulty with the student's personal profile, which includes such variables as cognitive ability and learning style. For instruction and technical education, the complex tutorial models provide for appropriate sequencing of the amount of practice with rule statements, examples, and problems, especially as these are integrated into highly complex behaviors.

Algorithmic Regression Models provide for individualized prescriptions based upon task, media, and learning variables. In essence, the regression-based learning prescription spells out a plan of instruction for each student. In addition, the Algorithmic Regression Models will assign appropriate incentive levels so as to optimize the motivational state of the learner. As an added feature, these models allow for optimal assignment of resources, given that one wants to maximize a common goal such as total progress of all students as opposed to maximizing the progress of an individual student solely.

Dynamic Programming Models provide for a sequential or multistage decision process that can incorporate many tasks, media, student, and resource variables. The dynamic programming models convert these multistages into a series of single-stage problems which can then be optimized. Most importantly, dynamic programming models provide for a hierarchical nesting of other adaptive models, and, in essence, function as the master model for AIS.

In addition to the above models, it was recommended that further research be directed toward extending *Natural Language Processing* and *Automaton Models*.

Natural Language Models provide a conversational dialogue between the system and the student. This dialogue requires a full representation of the student's language and mental processes. The interactive-contingent nature of the dialogue allows for mutual information clarification and stimulates the development of student competencies as he achieves mastery over given training objectives. Natural language processing models should also prove helpful in extending student evaluations to counseling processes within AIS.

Automation Models provide for the abstract theoretical representation of a student-training system. This representation is in terms of states that are defined by input and output relationships. From a monitoring and prediction point of view, automaton models represent the most advanced theoretical developments. Unfortunately, their operational representation is still exceedingly limited. Consequently, basic research progress will be necessary prior to full implementation within AIS.

II. INTRODUCTION TO ADAPTIVE INSTRUCTIONAL MODELS

Adaptive Instructional Models (AIM's) constitute means for individually prescribing, analyzing, and adapting instructional materials, tasks, and resources to differences among students on such dimensions as ability and motivation. The ultimate goal is to train competent Air Force technicians in the minimum time at a cost-effective level.

First, the AIM's serve as a representation of its characteristics and operations of the Advanced Instructional System (AIS). In that sense, AIM plays both the role of a model and of a simulation. More explicitly, the proposed AIM shall be implemented as synthetic training sessions which provide "Monte Carlo" data representative of student performance plus the training outcomes anticipated for AIS. Second, AIM's represent the mathematical tools whose formal processes and parameters allow for accurate predictions about the outcomes and adaptations involved in the AIS methods of training. In turn, the simulation aspects of the AIM's provide guidelines which can be used in the design and implementation of the AIS computer management system. Finally, AIM, when programmed, will provide code for the AIS operation as well as the first concrete, explicit example of the AIS performance recording data base necessary for contingent adaptive training procedures.

The payoff from AIM for the AIS project can be viewed in both short-and long-term benefits. For the short term, the principal benefit will be the clarification of adaptive training processes. This clarification will result from the detailed literature search and model identification provided within this document. Another benefit is that classes of adaptive models will be identified in terms of their purpose, their formal structure, and their potential payoffs. These elements are presented in Sections II through IX to allow for an initial consideration of which adaptive models to pursue within AIS. As indicated previously, the simulation aspects of this AIM study will provide design guidance as well as representation of actual AIS computer operations.

As for long-term benefits, AIM's provide the conceptual basis for this individualized form of technical training. Finally, AIM provides for a coherent paradigm for the multivariate requirements that functionally represent student characteristics, instructional modes, task characteristics, training decision processes, and the allocation of instructional resources.

Concept of AIM Within AIS

The AIM will play a general coordinating role in the AIS. It can be anticipated that the AIM will structure learning prescriptions based on student and task characteristics and monitor all students' training activities in order to provide input to the adaptive process. In addition, there is the potential for monitoring and optimally assigning learning resources, such as instructors, media devices, simulators, or instructional software. Thus, AIM is inextricably involved in all phases of the AIS operational environment.

AIM Characteristics

The Adaptive Instructional Models will have four properties that promote the individualization of the training process: adaptiveness, contingency, mediation, and cybernetic.

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AIM is *adaptive*, in that the training process will be individually tailored to each student. In operational terms, the training decisions will be made by continually choosing among instructional alternatives as a function of differential student characteristics, as measured by the AIS training process. The concept of adaptiveness will include the features of *selectiveness* since each student will be presented with information according to his needs in light of the terminal objectives, *sequenced* because the materials will be presented in an optimal sequence for each student, and *paced* since the student will be provided with a rate score commensurate with his prior performance and his learning characteristics. In addition, adaptiveness will include the concept of individually-prescribed media, amount and type of review, and use of remediational material.

In reference to the second feature, *contingency*, AIM will provide relationships which will consider *who* is being taught, *what* is critical in the subject matter, and *how* the teaching is to be done. This will include strategies by which student characteristics are matched with a catalog of training alternatives under the control of computer-based algorithms so as to prescribe optimal sequences. In addition, contingency will include the concept of individually-prescribed incentives according to performance related incentive schedules, as well as opportunities to branch or re-enter learning sequences according to identified levels of mastery.

The third general characteristic concerns the *mediation* process, which will include a wide range of media and learning formats configured to optimize the information flow according to specifiable subject-matter maps. In essence, the subject-matter maps will be defined in terms of task characteristics and will lead to an optimal matching of training resources in light of task features and student characteristics. Mediation will include the concept of appropriate media matches as well as individual and small group instruction. Where appropriate, the student may also be assigned to individual counseling sessions designed to facilitate the learning process.

An empirical feedback procedure which uses student data from established criterion measures to redefine parameters of the strategies and their embedded decision rules characterizes the *cybernetic* feature. Each student will be continuously monitored by AIM so that his profile identifies his current status as well as his best performance within various instructional strategies. The feedback of success and failures will not only be recorded for individual students but also will be aggregated so as to improve the overall modeling process for new groups of students. This continuous updating of student performance will improve the accuracy of both the individual learning prescription and the model's predictions of optimal learning sequences. Thus, AIM provides data which will cybernetically improve the performance of the model itself.

Computer-Managed Instruction (CMI) Model

As a framework, AIM must provide a proper flow so that students may be prescribed learning tasks in an individualized sequence. As presented in Figure 1, this adaptive instructional flow can be characterized by ten steps. The critical steps are concerned with the selection of an appropriate adaptive model and its application in the composition of an instructional prescription.

In reference to Figure 1, the AIM utilizes the following steps in individually guiding the students:

Step 1. The student's learning profile is updated based on immediately prior performance, learning time, and associated data from similar learning tasks.

Step 2. The current task characteristics with their associated behavioral objectives are retrived. Most importantly, these task characteristics will related propositional statements concerning the type and kind of learning processes involved.

Step 3. All available instructional alternatives for the associated instructional tasks are retrieved. Table 1 presents a list of the type of instructional alternatives which are being considered.

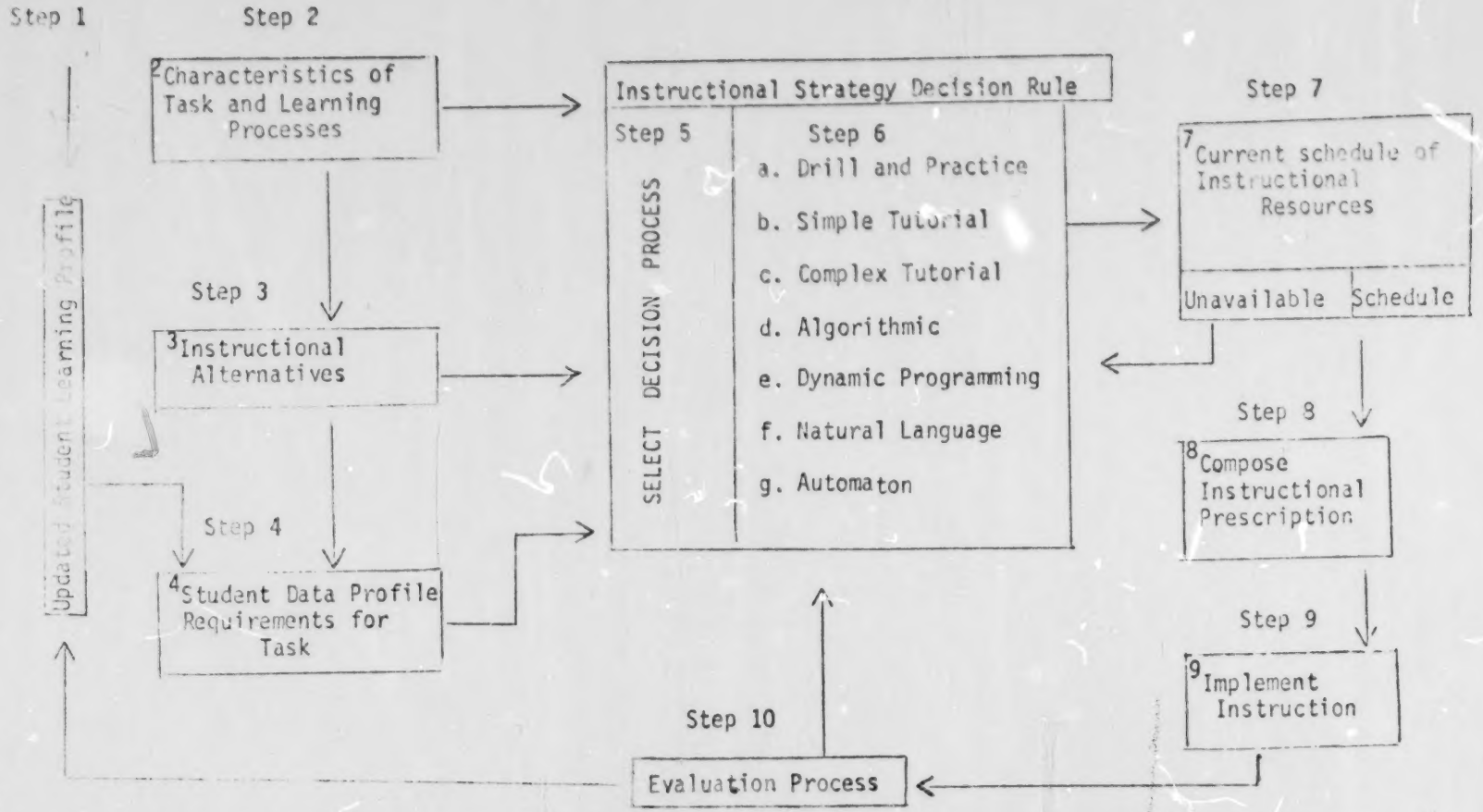


Fig. 1. Adaptive Model(s) Program Flowchart.

Step 4. Any essential student characteristic data present in the computer data base are retrieved if the data are likely to be utilized within the instructional decision process.

Step 5. An appropriate adaptive decision process based on effectiveness data from the prior application of the model for the task and the student is selected. In essence, an appropriate adaptive model for the task should be chosen.

Step 6. An appropriate instructional strategy is derived from the model. This strategy should provide for selection among instructional alternatives.

Step 7. The specific instructional alternatives are identified and checked as to their availability.

Step 8. An instructional prescription is transmitted to the student.

Step 9. The instruction proceeds.

Step 10. The evaluation of the student learning will supply critical data to the updated student learning profile and effectiveness data for the AIM's.

The flowchart can be successively applied for the task sequence. As illustrated in Steps 5 and 6, the essence of the flowchart concerns the different classes of adaptive models. Each of the models can be characterized both in terms of its purpose and its quantitative characteristics. Perhaps a brief review of the purposes will give some idea of the essential characteristics of each class or type of model.

The primary objective of the Drill-and-Practice Models is to increase the accuracy and speed of student performance on repetitive tasks. The primary objective of the Simple Tutorial Models is the acquisition of new conceptual behaviors. These behaviors may concern new definitions, dimension of concepts, and relationships among these dimensions. Complex Tutorial Models concern task situations involving two or more concepts, simulation representing the concepts, and/or problem-solving applications of the concepts. The primary objective of Algorithmic Models is to provide a systematic, efficient approximation toward some specific goal. On the other hand, Dynamic Programming Models provide for solutions that minimize learning time and offer the best utilization of resources. Natural Language Models have a primary goal of reproducing the dialogue between two human beings and, therefore, represent all the techniques and strategies utilized by a human instructor. Finally, Automaton Models strive for the full representation of all mental processes and their changes while training is administered.

TABLE 1. INSTRUCTIONAL ALTERNATIVES FOR ADAPTIVE MODELS

Alternative Method	Advantages
Alternative media presentations	Provides for the selection of appropriate media types at choice points having two or more available media treatments, e.g., film, slide-tape, video tape, text, lecture, computer-interactive problem solving, TV, and skill critique.
Type of interactive instruction	Provides for selection of a training activity that has the appropriate interactive rates and characteristics, e.g., PI, CAI, simulation, performance with equipment, instructor, tutorials, and student-to-student tutorials.
Entrance into a learning hierarchy	For those task sequences that have a generic learning hierarchy, the criteria for each entry point in the hierarchy will be identified and students assigned entry into the hierarchy according to their characteristics and current performance.
Sequence of topics in terms of level of difficulty	Provides for matching student performance characteristic with alternative topic sequences and associated redundancy levels, whether they are summary, normative, or elaborated.
Student and system control pacing	Provides for unique student-based training time limits for an instructional task (student paced) and for system pacing-assignments for computer-interactive training activities.
Amount of practice	For each set required of a student, the number of problems will be uniquely derived according to his performance history.

Relationships among Adaptive Instructional Models

The six proposed classes of AIM's are interrelated from two points of view. The first concerns commonly shared or unique training variables; and the second, the inclusiveness of the learning and resource allocation process. There appear to be five categories of variables that reflect the operational characteristics. These are (1) task characteristics, (2) instructional mode, (3) decision processes, (4) student characteristics, and (5) instructional resources. The category of task characteristics is highly similar to types of learning in that there is a specification of the training requirements from an informational point of view. Examples within this category would include items such as verbal information,, rules, problem sets, psychomotor tasks, and complex simulation tasks. The critical variable within-task characteristics concerns learning difficulty. For example, each type of learning will be reflected in a level of performance difficulty which will, in turn, influence training decisions such as the availability of prompts or the amount of practice. The models will vary as to the nature and complexity of the task that they can monitor and adapt.

Instructional modes include elements characteristic of a training session such as the directions for learning, the presentation of learning media and materials, type of student interaction (*e.g.*, pacing), and feedback. The critical variables in modes of instruction are concerned primarily with media, the type of interaction, and the feedback process.

The models vary as to the number of instructional mode variations they monitor and prescribe; drill-and-practice varies only with respect to pacing, while alogrithmic models attempt to prescribe all the variables.

The decision process is concerned with levels of precision and prediction according to the procedure, be it heuristic, algorithmic, or optimization. Another way of viewing the decision processes would include the concept of "sufficiency," *i.e.*, the degree to which the student's learning data and aptitude characteristics are utilized in the decision process. Thus, the more frequently individualized data are utilized in the decision process, the more complex and predictive the process becomes. Drill-and-practice models tend to use simple decision rules, while dynamic programming models employ complete and much more complex optimization routines.

The fourth dimension concerns student characteristics. These characteristics vary according to stable indices such as aptitudes and trait measures, semistable characteristics such as perceptual and learning styles, and task specific characteristics such as latency and anxiety. The models vary considerably according to the amount of information they utilize in the process of making decisions. In addition, the models vary in their treatment of the variable classes and the collection-update process.

The last category of variables concerns instructional resources. In essence, a model must construct a prescription which furnishes training resources to a given individual for the purpose of achieving a given training task. Again, models vary in the number and quantity of the resources being monitored and allocated, whether resources are traditional texts, PI texts, films, computer terminals, trainers, simulators, or human instructors. For the different models, there is a range of complexities in the allocation of resources. Thus, the five operational characteristics of task structure, instructional mode, decision processes, student characteristics, and instructional resources provide the salient differences that aid in distinguishing among the models and their potential for improving the training process.

Research Findings and Recommendations

It is fully recognized that in the succeeding sections of this report, specific, detailed, and operational recommendations are frequently made as if the research findings fully justify these at present. Clearly, the status of the research in the adaptive modeling area on which this report is based is far from being informationally or theoretically sufficient to justify each of the recommendations in all their operational terms. On the other hand, it is precisely these operational recommendations which are being sought. Ways to reconcile this paradox are (1) to create the best possible interpretation of the state of knowledge, and (2) to provide for future evaluations and revisions. It is anticipated that some of the recommendations made in the present report will have to be revised or dropped in the light of data accumulated in the future operation of AIS. For each of the model categories, extensive research is required to provide complete data, interpretation, and guidelines for practice. Nevertheless, since training has to be carried on in the present, the best available inferences from the existing data base have been made. It should be recognized that the remaining sections of this report do not make continuous cautionary notes regarding the incomplete data base in order to avoid unnecessary repetition.

III. DRILL-AND-PRACTICE MODELS

Characteristics of the Models

In general, drill-and-practice may be defined as the presentation of a series of similar items to which the student must respond within fixed time limits. In computer-administered drill-and-practice, immediate analysis of the response and provision for feedback to the student are possible. In the early 1900's, there was a great deal of emphasis on drill, in accordance with the "faculties" theory which dominated much of the educational practice of the day (Suppes, Jerman, & Brian,, 1968). In a paper summarizing 48 unpublished studies, Wilson (1925) concluded that a drill should contain the following attributes in order to be effective:

It should be on the entire process

It should come frequently in small units

Each unit should be composed of mixed items

It should have a time limit

Examples in a unit drill should be in order of difficulty

It should include verbal problems

It should facilitate diagnosis.

Drill-and-practice sequences presuppose the prior introduction of the concept or skill being drilled. Strategies have led to the insertion of drill-and-practice at three different points in the sequence of instruction. These points are (1) immediately after the concept or skill has been introduced, (2) at a time when remedial instructional treatment is required, and (3) periodically as a review of the concept or skills previously introduced.

Drill strategies are appropriate for several different types of learning. The performance required of the student may involve rote recall such as learning arithmetic tables, spelling words, foreign language vocabularies, and symbols for chemical elements. Another application is to facilitate learning rules or algorithms such as those involved in arithmetic operations, grammar, and the formation of chemical compounds. Even high levels of learning such as the abstract reasoning involved in solving verbal analogies or troubleshooting can also be handled using drill techniques.

The two primary goals of drill-and-practice strategies are to improve the student's accuracy and to increase his speed of performance. Both of these goals are consistent with the objectives of AIS. During the AIM project, three categories of drill-and-practice models have been identified as being most useful and feasible for the AIS. These categories include pacing, domain-sampling, and domain-exhausting. Pacing models are characterized by the utilization of techniques for controlling the presentation rate of drills based upon individual history. A specific model for pacing of reading is presented in this report. Much of the literature on individualization has speculated on the value of reading at one's own pace. The model discussed utilizes procedures which quite possibly may be more effective than learner self-pacing.

The other two types of models are more concerned with drill content rather than time. The domain-sampling model draws items from a large pool, whereas the domain-exhausting model utilizes all possible items (content wise). The distinction between domain-sampling versus domain-exhausting drills is significant because the decisions within the two strategies are different for item sequence, level of difficulty, termination criteria, and number of items presented.

Role in AIS

Several applications for drill-and-practice are evident within the context of AIS. In the Precision Measurement Equipment (PME) course, drill-and-practice techniques would be useful for instruction in basic mathematics, for teaching definitions of terms, for performing calculations (*e.g.*., calculate voltage, current, and resistance in a series DC circuit), for converting units of measurement, and for reading meters (depending upon the availability of some sort of visual-display device). In the Weapons Mechanic Course, the procedure could be used for elementary topics in electricity. If visual display devices are available, drill-and-practice techniques could be used for identifying weapons from photographs or parts of circuitry

from schematics. Applications in Inventory Management include drill in the use of coding schemes and the classification of information according to security rules.

Payoff

The payoffs for drill and practice adaptive models are consistent with major objectives for the AIS and are readily stated. At a general level, increases in speed and in accuracy of performance in a range of tasks varying from simple to complex are two of the possible payoffs. These are gains above the standard self-pacing or group-rating instructional strategies, and they increase the viability of AIS goals for a cost-effective, individualized system. Furthermore, the models are embedded in strategies for review and remediation which are especially important in a technical training environment.

Literature Review

This section summarizes the literature related to computerized drill-and-practice models.

Drill-and-Practice Implementations

Stanford Project. In January 1963, the Institute for Mathematical Studies in the Social Sciences at Stanford University began a program of research and development in computer-based instruction. The first operational instructional program was in elementary mathematical logic. During the 1964-1965 school year, arithmetic drill-and-practice materials were developed and tested. This drill-and-practice program was expanded, and it has now been implemented with thousands of students at remote terminals scattered around the country (Suppes, Jerman, & Brian, 1968).

The Stanford curriculum was divided into concept blocks which were further subdivided into lessons consisting of 20 items. The blocks were arranged to correspond to the topics in conventional textbooks, and the initial instruction on all concept was given by the teacher. For each item, the student was given three opportunities to respond correctly within a 10 second time limit before he was given the answer. The next exercise was then presented. Feedback consisted of messages such as "WRONG," "TIME IS UP," and "WRONG, THE ANSWER IS: ." A student would complete one lesson each day with an average of 5 minutes for each session at the terminal. Lessons were prepared at each of five levels of difficulty within each concept block and organized according to the diagram shown in Figure 2. Those students who scored above 79 percent correct on a lesson moved to the next higher level the following day. Students scoring between 60 and 79 percent stayed at the same level, and those scoring below 60 percent were given a simpler lesson at the next lower level.

Current projects at Stanford directly attack the problem of adaptation. Adaptive teaching systems (Laubsch, 1969) which can control the learning process by item presentations in an optimal sequence have been studied. In addition, new research has recently begun on structural variables which reflect information-processing attributes of humans when presented with a sequence of instructional presentations (Loftus, 1970; Atkinson & Juola, 1971; Jerman, 1971). These attributes are especially relevant to sequencing drill-and-practice so as to maximize gains in speed and accuracy.

Kansas City. A slightly different approach to using drill-and-practice techniques was taken by the Kansas City, Missouri public school CAI Laboratory. Most of the lessons were tutorial in nature, but frequently they contained drill-and-practice sequences. The lessons were classified as either required or elective and were organized into blocks of approximately 12 weeks' duration (40 to 60 minutes/week). Since no attempt was made to keep students together, there was only a rough correspondence between lesson topics and classroom instruction. Each block began with a lesson on using the basic operations with whole numbers, fractions, of decimals which was primarily in the drill-and-practice mode. The objectives of these initial basic skill lessons were twofold: (1) to screen out those students who had not yet mastered these prerequisite skills and, consequently, would be unable to succeed in later lessons in the block; and (2) to act as a refresher for those students who were already close to reaching criterion. Complex pretesting strategies were utilized to minimize testing time. Some students were able to finish such lessons in as little as 20 minutes, while other students required 5 hours or more. As time passed, the distribution of students over lessons within a block became even greater. While this approach only individualizes instruction by adapting to entry behaviors and allowing self-pacing, it promises great payoff for AIS, particularly in courses where entering students vary greatly in experience and ability.

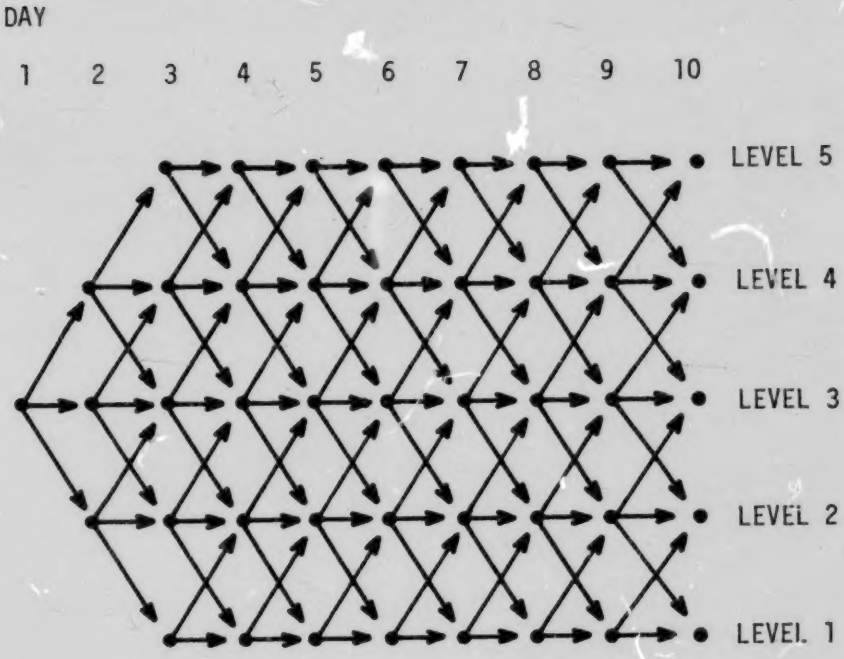


Fig. 2. Diagram of Branching Structure Followed in Constructing Sets of Exercises for Concept Blocks (Suppes, Jerman, & Brian, 1968).

The several lessons that were implemented in Kansas City included mechanisms to adapt the drills to the individual students on the basis of within-course performance variables such as latency and achievement. In a remedial drill on multiplication facts, an algorithm was included to adjust the time allowed for response input on the basis of recent response latencies and the accuracy of the immediately preceding response. Such a performance-contingent pacing condition was intended to improve the student's speed of responding without sacrificing accuracy in a task which is basically memorizing the multiplication table. In the same drill, a mechanism was included to note the particular stimulus items to which the student was responding incorrectly. These items were then presented more frequently than would have occurred by chance (*i.e.*, if all items were composed by a random number generator). Consequently, the student received a greater proportion of items for which it was known he needed practice. At the same time, these difficult items (for that particular student) were interspersed with randomly composed items to (1) give the student some successful experiences and (2) locate other troublesome items.

Several adaptive strategies were employed to determine the number of items to be presented in each drill. These strategies were typically based on cumulative achievement indices within each drill such as (1) continuing to present items until the student gives a specified number of consecutive correct responses and (2) beginning with a given number of items for a drill and incrementing this index for each incorrect response and reducing it for each correct response until the index either reaches zero or becomes so high that remedial instruction is indicated.

In one lesson, the criterion for passing a drill was dynamically adjusted according to the number of times the student had attempted that particular drill. This strategy was employed to avoid trapping a student in an instructional sequence which was not effective for him and, concurrently, the proctor was

notified that some alternative instruction should be provided for this student. In Kansas City's curriculum, the feedback consisted of a series of hints or prompts designed to lead the student to the correct answer. It the number of incorrect responses to an item exceeded the number of hints (usually four or five), the student was shown the correct answer and was required to type it in before continuing to the next exercise.

In addition to these two projects drill-and-practice sequences have been developed for many different installations. Most numerous, perhaps because they are easiest to develop, are the drill-and-practice lessons in elementary arithmetic skills. Stanford began its arithmetic drill-and-practice program in the spring of 1964 (Suppes, Jerman, & Brian, 1968). Other examples of arithmetic drill-and-practice may be found at IBM Education Research Division, San Jose, California (Barnes, 1970; Dean, 1969), Leeds University (Woods & Harley, 1971), and Wakulla County, Florida. (Hansen, Johnson, Durall, Lavin, & McCune, 1971).

In the language arts area, drill-and-practice has been used for reading at Stanford (Atkinson, 1967), Wakulla County, Florida. (Hansen *e al.*, 1971) and City University of New York (Schiavone, Rowen, & Farrell, 1971). Research in spelling drills has been conducted at Stanford (Fishman, Keller, & Alkinson, 1969). Drill-and-practice courses in foreign languages have been developed at State University of New York, Stony Brooks (Morrison, Adams, 1969; Adams, Morrison, & Reddy, 1969).

A rather unusual application of drill-and-practice has been reported by Hullfish at State University College, Brockport, New York (Hullfish, 1971). He proposed that drill strategies may be used to teach abstract concepts. He described a drill-and-practice program in verbal analogies which explains the logic behind each example in an effort to improve the students' abilities to solve them.

Learning Effectiveness

The learning effectiveness of various strategies associated with individualized learning has been investigated along five dimensions relevant to drill and practice models. These dimensions of pacing, learner control, massed versus distributed practice, overt correction, and item difficulty are discussed in the following subsections.

Pacing. Previously, the capability of learning at one's characteristic rate was generally acknowledged to be an important aspect of individualized instruction. However, this review specifies the lack of empirical evidence supporting self-paced instruction, and the relative ineffectiveness of current alternatives to self-pacing, and discusses an alternative based on performance-contingent pacing in computer-assisted instruction.

The following review begins with a consideration of self- and fixed-paced instruction. Next to be reviewed are those studies which investigated the effects of various externally applied tempos on performance in programmed instruction. This review is then followed by a discussion of a method of maximizing learning effectiveness and efficiency in computer-based instruction by using pacing.

Learning with Self- and Fixed-Paced Instruction. Feldhusen and Birt (1962) presented college students with a 37-frame linear program. Two conditions were employed—one condition permitted students to pace themselves, while the other forced the students to proceed at a predetermined pace. The pace for the latter condition was determined by the average time per frame required by subjects who worked through the program at a self-adopted rate. No statistically significant achievement score differences were found between the self- and externally-paced rate employed.

Carpenter and Greenhill (1963) investigated the effects of self- and fixed-pacing on achievement in a 15-unit mathematics course. The externally-paced group was presented frames at a rate based on the average rate of a pilot group of students who studied the program at their own rates. Under these conditions, no differences in final achievement between the self- and externally-paced groups were observed. In contrast to the preceding findings, evidence from a series of studies (Locke & Bryan, 1969) consistently indicated a statistically significant performance difference in favor of externally assigned (incremented fixed rates) as opposed to self-assigned performance rates. Though incentives appeared to not influence performance directly, such incentives were significantly related to performance intentions measured prior to actual performance. It may be that incentives persuade an individual to accept assigned difficult tasks with a subsequent increase in his performance, whereas self-selected performance rates do not sufficiently challenge the individual's performance capabilities.

Kress and Gropper (1964; report No. 1) investigated individual differences in learning from self-paced programmed instruction. In this investigation, two 100-frame science programs were administered to two groups of eighth graders. Individual difference variables such as IQ, reading comprehension, and entry level were investigated. Data indicated that self-adopted fast paces were related to poorer performance than the performance of students whose self-adopted pace was slow. Most of the variability, however, occurred among low IQ students, suggesting that low IQ students who were permitted to pace themselves did not benefit from self-pacing opportunities. Also, it should be pointed out that many high IQ students worked at a slow pace; thus, they were extremely inefficient, even though they performed well. Another important observation from the Kress and Gropper study was that students tended to be consistent in the work rate which they adopted. The average correlation between work rates on the two instructional programs in this study was 0.80. In addition, students were consistent in the number of errors which they made on different programs, as evidenced by a correlation of 0.78 between the number of errors made on the two instructional programs. These correlations may indicate that work rate is idiosyncratic in nature and reflective of the student's characteristic reading speed and work habits.

Since the preceding study suggested that some high- and low-ability students failed to profit from self-paced rates, the use of such rates in the determination of fixed rates is dubious. It is reasonable, therefore, that Feldhusen and Birt (1962) and Carpenter and Greenhill (1963) found no differences between self- and fixed paced groups. Studies which did not determine fixed paces on the basis of rates established during self-pacing are reviewed below.

Heyel (1967) designed a study to compare the effectiveness of self-paced and group-paced instruction in teaching a manipulative skill and related cognitive information. Students receiving the group-paced instruction were permitted to progress only after the last person in the group responded to a frame. A cognitive and a performance test were administered immediately and at 2 and 6 weeks following instruction. Heyel observed no differences in performance, students using the group-paced instruction required less time to complete the learning task than did the last individual in the self-paced group.

Gropper and Lumsdaine (1961) compared programmed instruction presented at a fixed pace with a lecture version of the same lesson. The programmed instruction material resulted in higher achievement than the lecture; however, this difference was due primarily to the high-ability students in the programmed group. That is, high-IQ subjects showed large performance gains from programmed instruction, whereas low-IQ students in the programmed instruction group did not differ in performance from low-IQ students who received the lecture. For the rate employed, this study indicated that when heterogenous students are paced at a fixed rate, high-ability student performance increases, but low-ability student performance remains comparatively poor. A lack of adaptability to individual differences in ability and characteristic reading rate may be the reason that certain fixed-paced rates were found ineffective for low-ability students.

Frye (1963) argues for the use of homogenous groupings. He investigated the effects of group and individual pacing for homogenous and heterogeneous groups on the rate of learning in programmed instruction. All students were required to achieve the same criterion. Homogenous groupings in this study were based on IQ and predicted algebra ability. Frye reported the following findings:

- Students in the group-paced heterogeneous group took significantly longer to complete the program than the self-paced heterogeneous group
- The homogenous group which received self-pacing did not differ from the homogenous group which received group-pacing did not differ from the homogenous group which received group-pacing in the time required to complete the program
- The heterogeneous group receiving group-pacing took significantly longer to complete the program than did the homogenous group-paced students.

Thus, only where there is a wide range of abilities represented within a group of students is there a chance that the learning rate will be retarded by external pacing procedures. However, since this study used only the learning rate as the dependent variables, the effects of group and individual pacing for homogenous groups on achievement or errors are not known.

The results of studies reviewed so f... may be summarized as follows:

- Self-selected rates are often inappropriate for both high- and low-ability students; however, more definitive research is needed.
- Fixed paces based on self-paced rates are incompatible with high achievement for many students
- Fixed paces not based on rates established under self-paced procedures do not improve the effectiveness of the instruction, resulting in only small gains in efficiency
- Low-ability students are adversely affected under both self- and fixed-paced instruction.

The next section reviews those studies which employ various presentation tempos in an effort to optimize learning effectiveness and achievement.

Variations in Tempo. Silverman and Alter (1961) conducted a study which compared two fixed-paced groups and one self-paced group. One fixed-paced group was paced at a rate slower than necessary for most of the students. Finding no differences between any of the groups led these investigators to conclude (page 41) that "pacing the learner will not impair his performance if care is taken to ascertain optimal pacing rates."

In a 1963 companion experiment, Carpernter and Greenhill investigated the effects of various presentation tempos on performance in six programmed mathematics units. The tempos chosen were 80, 90, 100, and 110 percent of a base tempo, defined as the mean time required per frame by a pilot group who worked through the same materials at a self-adopted rate. Measures of both achievement and attitude toward instruction served as dependent variables. No differences in performance or attitude were reported for any of the four pacing tempos. Nonsignificant differences in achievement were also observed in a study by Nicholas (1966) which employed rates of 50, 75, and 100 percent of a base tempo. In a more recent study, Blackwell (1970) found no differences in performance between students taking three (normal, slow, fast) versions of a machine-paced sound/filmstrip program.

The effects of presentation rates ranging from 150 to 350 words/minute on learning from audio, visual, and audio-visual modes were investigated by Jester and Travers (1966). Comprehension scores for all modes decreased as the presentation rate increased. Similar results were observed by George (1970) and Rossiter (1971) in studies on learning from compressed speech.

One of the most comprehensive studies on the influence of external pacing on learning from programmed instruction was conducted by Kress and Gropper (1964, report No. 2). The aims of this study were: "determine whether students differing in ability or characteristic (self-paced) work rate experience (the effects of external pacing differentially) and to compare the relative effectiveness of fixed- and self-paced program instruction." In this study, eighth-grade students were presented a 100-frame program on electricity under either a fixed rate of presentation or in booklets at a self adopted pace. Three versions (slow, medium, fast) of the fixed-paced presentation were prepared. Preliminary self-paced programs were administered to determine the students' self-paced or characteristic work rates. Only those students who reached an achievement level of 70 percent on the preliminary program were retained for the main experiment. The observed work rate, then, was one which permitted a relatively high level of achievement. The observed results indicated that increasing the tempo resulted in increases in average error rate, which did not rise above 16 percent for any condition; also, there were no decrements in achievement as tempos increased. Kress and Gropper suggest that achievement would be affected adversely if, as a result of increasingly fast tempos, the error rate became sufficiently high.

It was further observed (Kress & Gropper, 1964, report No. 2) that when characteristic work rates were controlled, high-ability students performed better than low-ability students; and as tempos increased, the differences between these groups increased as well. Another finding (contrary to Kress & Gropper, report No. 1) was that characteristically fast students outperformed characteristically slow students. This superiority of characteristically fast students was evidenced by fewer errors and higher achievement scores. Interestingly enough (since all students were "qualifiers"), students who paced themselves performed poorer than students in the slow fixed-pace condition.

These results indicate that, among other things, work rates may be inappropriate under both self- or fixed-pace conditions. That is, self-paced students often adopt a rate which is too fast for accompanying high achievement, and, under fixed-pace conditions, students may be required to work at rates which are too fast and not compatible with achievement. In addition, increasingly fast tempos appear to impair the learning of low-ability learners.

Performance Contingent Pacing. It has already been pointed out that Kress and Gropper (1964, report No. 1) found individual readers to be consistent in the pace they adopt. This consistency suggests that forcing subjects to a more nearly optimal rate through an adaptive performance-contingent procedure could have beneficial effects on later self-paced reading. If near optimal rates could be externally established, a reader might tend to maintain the rate under self-paced conditions.

Brown and James (1972) investigated one strategy for optimizing information presentation rate. A self-paced (SP) condition and a performance-contingent (PC) condition were utilized. Students read 40 passages presented via cathode-ray tube and responded to three multiple-choice questions following each passage. One group received the first 20 passages under a performance-contingent presentation condition followed by the next 20 passages under a self-paced condition. Another group received the same two conditions, but in the reverse order. In the performance-contingent condition, the presentation rate of the passage was manipulated on the basis of the student's performance on the proceding passage's questions. The following decision rules were employed:

- If the student answered all three questions correctly, the rate was incremented for the next passage
- If the student answered less than two of the three questions correctly, the rate was decremented
- If the student answered two questions correctly, and if he answered all three questions correctly on the previous passage, the rate remained unchanged for the next passage.

It is of interest to note that the SP condition following the PC condition resulted in the highest retention performance observed and in a reading rate faster than the SP first condition, suggesting a carryover from the PC condition into the following SP condition. This carryover effect is also seen as having given rise to the interactions between order and pacing and to be consistent with other findings which indicate that subjects tend to be consistent in the pace which they adopt (Gropper & Kress, 1965). Slightly longer latencies for the PC condition indicate subjects were employing a longer recall interval as would be expected given the higher mean presentation rate in this condition.

The apparent carryover effect and the absence of undersired effects on anxiety or attitude, coupled with only slightly lower retention scores in the PC condition, suggest that performance-contingent pacing could be a valuable alternative to self- or fixed-paced instruction.

Learner Control. The research on learner control over sequence has shown that those students in a learner-control condition usually score equivalently on a posttest with those students taught under an author-controlled sequence. It has been reported that a small percentage of students, when given the opportunity, sequence materials differently than instructors would sequence them. Students in a learner-control condition tend to take equivalent or less time to learn the materials than those learning with sequences under instructor control.

A variable of some interest is the amount of control the student should have over the instructional sequence.

The sequencing and student-control variables have been investigated by Barnes (1970), Dean (1969), Mager (1961), Mager and Clark (1963), Kapel (1965), Grubb (1968, 1969), and Judd, Bunderson, and Bessent (1970). Dean (1969) using an elementary arithmetic task, reported that learner-control subjects had superior performances and, depending upon grade level, practiced less than students given a fixed linear task. Barnes (1970) concluded that learner control of amount of practice could lead to time savings if (1) the learner is ready to assume control and understands his option, (2) the material is meaningful and relevant, and (3) the learner is motivated to learn the material.

Mager (1961) was interested in whether individual students, when given the opportunity to control their own sequence of instruction, would generate a sequence similar to that devised by the instructor. In his study, six adult Ss with educational backgrounds varying from a high school graduate to a Ph.D. independently learned some electronics principles from an instructor. Complete control over the content and sequence of the curriculum was left to the student. The instructor answered questions and provided instruction, examples, and problems only at the student's request. An average of four 65-minute sessions were held for each S. It was found that (1) the learners tended to begin the course with a topic different from that usually selected by the instructor, (2) there was some similarity between learners in content sequences, and (3) the learner-selected topic sequence was not similar to that appearing in the usual electronics curriculum. These findings suggest that motivation might be enhanced by allowing the learner some control over sequence and content. The learner is thus studying at a point in the curriculum where he chooses to study, and is perhaps more receptive to the material.

In another experiment in which learner-control was investigated (Mager & Clark, 1963), students in an industrial training program were provided with a detailed list of terminal objectives. There were then told that they could ask anyone in their department for information related to the objectives. A shorter training time resulted for these students, and it was concluded that the students were better prepared than a group of students that had graduated from the normal job-training program. On the basis of this and other evidence reported in their paper, the authors concluded that students can learn on their own, and that the adult student, at least, can be a good judge of what he needs to learn and how he should learn it.

Kapel (1965) used linear programs in history to investigate learner control of sequence with 40 ninth-grade students. One group used the PI text in the usual manner, progressing through the program in a linear manner. The experimental group was encouraged to search ahead in the text at any time for information. The Ss in the nonsearching group scored higher on a test of initial learning, but the Ss who were encouraged to search ahead for information were superior on a retention test administered 1 month after completion of the program. Apparently, the learner given some amount of control over sequence can organize materials in a manner which is more effective for his own objectives. Grubb (1968) has hypothesized that the adult learner can structure such a curriculum which is suited to his own needs. The desirability of a learner-controlled course, wherein a map is presented and the student is permitted to inquire into different levels of a course, was discussed. The author suggested that motivation would be enhanced by such a procedure because the learner would be in a part of the course because he chose to be there.

Grubb (1969) reported a test of the learner-control hypothesis. In an IBM training program, two chapters in elmentary statistics were taught by computer-assisted instruction to 50 adults. In this program, 50 Ss were each randomly assigned to one of five conditions. Each chapter of the materials could be learned under either a linear sequence or a sequence under the complete control of the student. All permutations of learner control and linear format were represented, as well as a condition in which Ss could control both between and within-chapter sequence. It was found that complete learner control produced higher mean performance than conditions employing lesser degrees of learner control. Performance was degraded as the degree of learner control decreased, except for the condition where learner control was permited *within* both chapters, but not between them.

Learner control of instructional sequence, then, is a condition that has produced promising results. For those students capable of sequencing materials between chapters, the option is open, and they can take advantage of the opportunity to jump ahead or back as required. It has been shown (Mager, 1961), that students choose different paths through a curriculum. It has also been shown (Mager & Clark, 1963; Grubb, 1969) that students perform well when choosing a sequence. Student control, then, is seen to be an important factor in performance, at least for the materials that were investigated.

According to Judd (1970), any conclusions drawn about the relative effectiveness of the various learner-control options must be qualified due to the students' inexperiences with relatively unstructured learning situations. He also suggests that if students are to be given the option of deciding whether or not to enter a particular instructional segment, basing the decision in part on the results of a diagnostic pretest, they should also be given control options within the instructional segment. Otherwise, there is a tendency for the students that do need the instruction to avoid entering the instructional segments. Judd found that students who were given the option of terminating instruction performed at least as well as those who were required to reach criterion before exiting from an instructional sequence. He therefore concludes that

students are indeed competent judges of the amount of practice which they require on given topics. On the other hand, allowing the students to determine which instructional topics to investigate and the order in which these topics are taken appears to have had little beneficial effect, as compared to the predetermined sequence. Judd further elaborates on this result by noting that students tend to select topics for further study on which they have had some prior success as indicated by a higher pretest score. According to Judd, simply introducing the student to the topic appears to greatly increase the probability that the student will persist in studying that topic. Therefore, a degree of programmed control which at least leads the student to the topic may be preferable in situations in which the student has relatively little competence.

Massed versus Distributed Practice. The spacing of drill exercises is another question which has been investigated. When the items for a drill constitute a finite pool, there are many questions regarding the optimal order and number of presentations. With the same number of presentations for each item in a computerized spelling drill, distributed practice resulted in better performance than massed practice (Fishman, Keller, & Atkinson, 1969).

Another issue which received considerable attention was that of the desirability of using isolated (one concept only) versus mixed (several concepts at a time) drills. Repp (1935) recommended that isolated drills be employed following the introduction of a new topic or for remedial work, while mixed drills are better for maintaining skills. Suppes (1968) concluded that the optimal block size for learning a list of simple items depends upon the relationship between rates of learning and forgetting. The block size should be large when learning occurs faster than forgetting and small when the reverse situation is true.

Overt Correction. Overt correction may be defined as requiring the student to enter the correct response after he is given feedback on an incorrect response. There is some evidence that requiring an adult subject to make an overt correction response after reinforcement has no effect on his learning rate nor achievement (Burke, Estes, & Hellyer, 1965). In an experiment with young children, however, the learning curves for the two groups show a significantly faster rate of learning for the overt correction group throughout the entire experiment (Suppes & Ginsberg, 1962).

Item Difficulty and Structural Variables. While drill-and-practice implies a homogeneous set of items, there are frequently variations in difficulty within a pool of items. It, therefore, becomes necessary to determine the difficulty of items in a fixed pool and to predict the difficulty of items to be randomly composed. Two methods have been used to determine item-difficulty indices. One is based on an analysis of student response behavior on previous administrations, and the other is based on an analysis of structural variables or characteristics of the task (Maloney, 1962). For vertical addition problems (Woods & Hartly, 1971), the behavioral indices were (1) probability of success and (2) rate of work in each column. The structural variables which proved to be significant were (1) digit size and (2) number of rows. Cohen, Craun, and Johnson (1971) described the difficulty of spelling items, with a tentative list of 23 predictor variables. These structural analysis variables appear to be quite promising in terms of scaling and in sequencing items from easy to difficult.

Drill-and-Practice Models for AIS

With the preceding research literature and the experiences of educators at both Stanford University and the Kansas City Public Schools as background, two drill-and-practice models appear to be viable for AIS. These two models are described in terms of input variables, the model's processes, and the nature of the output. The first model is concerned with pacing of students, thereby controlling and facilitating the rate by which the learner completes the instructional lesson. The second model is more traditional in that the decisions concern the number, sequence, and difficulty of the drill-and-practice items, the nature of feedback, and drill-termination procedures.

The Pacing Model. The pacing model used by Brown and James (1972) (Figure 3) was developed on an intuitive basis, and, although it seems to be functioning satisfactorily, there are two considerations which point out the need for further refinement of the model.

First, no provision was made within the model to take into account an established characteristic reading rate for each individual. If such a pacing procedure were to be embedded in on going instruction, a base rate provision would be advisable. Second, the decision struction of the model needs to be revised such that the optimal rate for each learner is identified as rapidly as possible. A rapid identification of the

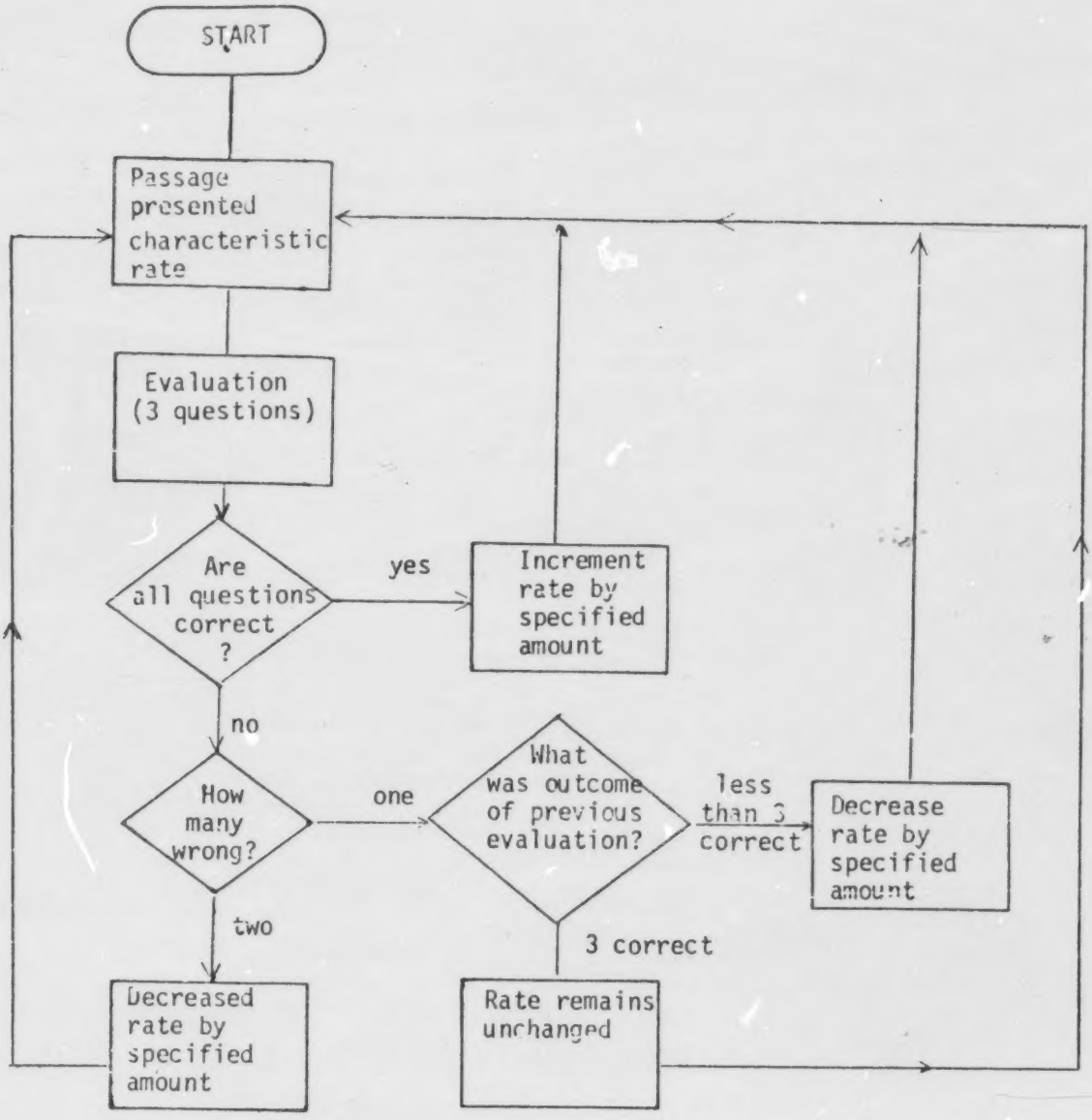


Fig. 3. Adaptive Pacing Model.

optimal rate will yield greater instructional effectiveness and efficiency. Furthermore, after the optimal rate is located, the decision structure should stabilize the presentation rate. More sensitive adjustments must be included in the model to ensure rate stability so that an individual's optimal rate will be approximated to the greatest possible extent.

Input. The suggested pacing model begins with a determination of the learner's self-paced, or characteristic rate of reading in terms of the number of words read per minute. The accuracy with which the student reads a given passage, in terms of both comprehension and word-for word accuracy, will also be measured and retained by the computer system. These measures may be considered as state variables. The trait characteristics to be measured may include reading style, reading level, verbal aptitude, and vocabulary. Measures which already exist in computer files will also be utilized. These measures include AQE scores, background measures such as SES, or motivation levels.

Processes. The rate of reading which is measured at the outset of instruction will be utilized to begin the search for an optimal pacing level together with the input variables listed previously. On the basis of the learner's performance in the task, as well as on trait measures, the presentation rate will manipulated; some rates will be increased, while others will be decreased in an effort to find the optimal rate. The outcomes of the pacing model, then, are reading rates which are more optimal than rates in a self-paced mode. This more optimal reading rate means that the performance has been maximized without creating detrimental effects on efficiency.

The pacing model presented here may have applicability for a wide range of instructional tasks. Essentially, when one or more paragraphs of written material are presented to a student, his reading ability becomes a factor in determining his performance. The pacing model would not be limited to one adaptive instructional model, but would be utilized whenever appropriate. An additional feature of the model is that the students' reading rate will be continually monitored both for adaptive use within the model itself and for use in other models as well.

Output. The pacing model has as its goal the facilitation of reading speed without the sacrifice of reading accuracy. The model will facilitate the attainment of this goal by providing output in the form of reading rate data which can be of use to instructors and as input to other adaptive models. From the students' perspective, the model is expected to increase reading rate.

Traditional Drill-and-Practice Models

The variables related to drill-and-practice instruction are divided into two classes, namely, task variables which relate to the nature of the instruction; and student variables, which describe individual student characteristics. Both task and student variables are used as input to the drill-and-practice adaptation procedure. Performance variables are also utilized within the drill-and-practice lessons to facilitate the adaptation process. The following paragraphs describe the input variables which will be used, the decision processes which will be employed, and the output that can be expected from the traditional drill and practice model.

Input. The input variables are categorized as student, task, and instructional variables. A student variable, such as reading level would be crucial for determining the means of communicating directions and the amount of text in the presentation of items. Aptitude and IQ will be used to predict the amount of practice necessary and the optimum rate of increasing item difficulty. Diagnostic information regarding the specific task not only answers the question of whether or not the student needs the drill, but also aids in specifying the initial range of item difficulty. Personality traits such as perseverance, and indices such as learning style will be used to determine the degree of learner control of instructional parameters. As a specific adaptive system is designed, other potentially profitable student variables may be identified.

The identification of task variables depends on an analysis of the task characteristics. However, some general variables may be specified such as item difficulty. Other task variables include the size of the item pool and the task requirements affecting the establishment of performance criteria. Task characteristics will also influence the choice of terminal device since some tasks require audio or visual presentation.

While student and task characteristics remain fairly static throughout a drill, instructional variables are generated by the drill itself and, consequently, are constantly being updated. They may be thought of as state indicators. Included in this category are items such as cumulative and recent indices of performance, response latency, item difficulty, location in item pool, and number of problems presented. The state of these indices for the n^{th} item is used as input for decisions regarding the n^{th+1} problem.

Process. There are many opportunities for adaptive decisions within a drill-and-practice sequence. These decisions include the following:

- How many items should be presented?
- How should the items be sequenced?
- What is the difficulty of each item?
- How much time should a student be allowed for each response?
- What kind of feedback should be given?
- When should a student exit from a drill-and-practice sequence?
- What are some criteria for predicting mastery?

One may categorize drill-and-practice models as one of two distinct types on the basis of the domain of items involved. The term "domain-sampling" model will be used to refer to drill sequences in which the items are randomly generated or drawn from a very large pool of homogeneous items. Drills in arithmetic would be included in this category. Chemical symbol drills, however, involve a finite list of elements for which the student will receive practice on every item in the pool. Drills of this nature will be categorized under the "domain-exhausting" model. The selection of the appropriate model is dependent upon the task involved. The distinction between domain-sampling and domain-exhausting drills is necessary, because the decisions inherent in these two models are different with respect to the number of items presented, item sequence, determining item difficulty, and criteria for terminating the drill.

For the domain-sampling model (Figure 4), the number of problems presented could be fixed for all students based on some heuristic decision, or predetermined for each student based on an algorithmic procedure using input variables to predict the optimum number of items for that student. Another alternative would be to dynamically adapt the number of items presented on the basis of the student's performance within the drill. For this latter alternative, it would seem feasible to employ a procedure such as Wald's Sequential Probability Ratio (1950) for predicting mastery at which point the drill may be discontinued. Another possibility would be to allow the learner to control the number of times an item is presented. It is possible that one could predict on the basis of input variables (learning style and prior performance) whether it would be better to specify the system control or specify the learner control (Barnes, 1970).

Since items in a domain-sampling model are frequently randomly generated or otherwise composed according to a specified format, it is not likely that a difficulty index determined on the basis of previous administrations will be known for each item. Consequently, item difficulty indices must be based on an analysis of structural variables such as the number of components, difficulty of each component, and complexity of relationships among components.

Several options are available regarding the sequence of items. The simplest drill would present a set of homogeneous items without regard to item difficulty. Another alternative is to order the items from easy to hard with the rate of increasing difficulty either fixed or predetermined for each student on the basis of input variables (ability and aptitude). Also, a difficulty range could be specified for each person on the basis of diagnostic information and student characteristics. In any event, any deliberate increment in item difficulty should be performance contingent.

For the domain-exhausting model (Figure 5), the number of items to be presented depends on the total number of items in the pool. The relevant question for this model is to ask how many times each item should be presented. Should a subset of items be identified as an "active" pool and, if so, what is the optimum size? If the optimum size varies from student to student, what variables are needed to predict it?

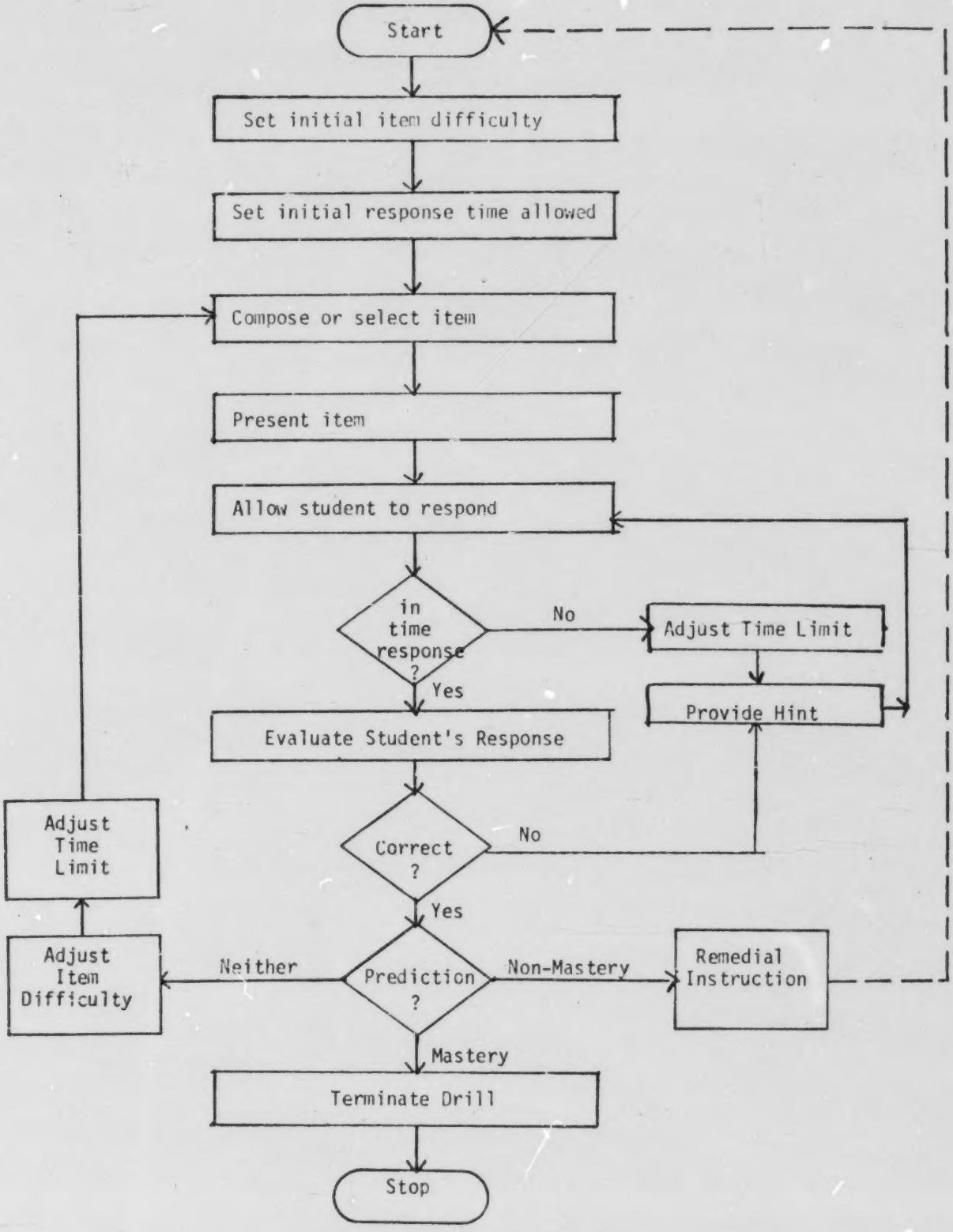


Fig. 4. Domain-Sampling Model.

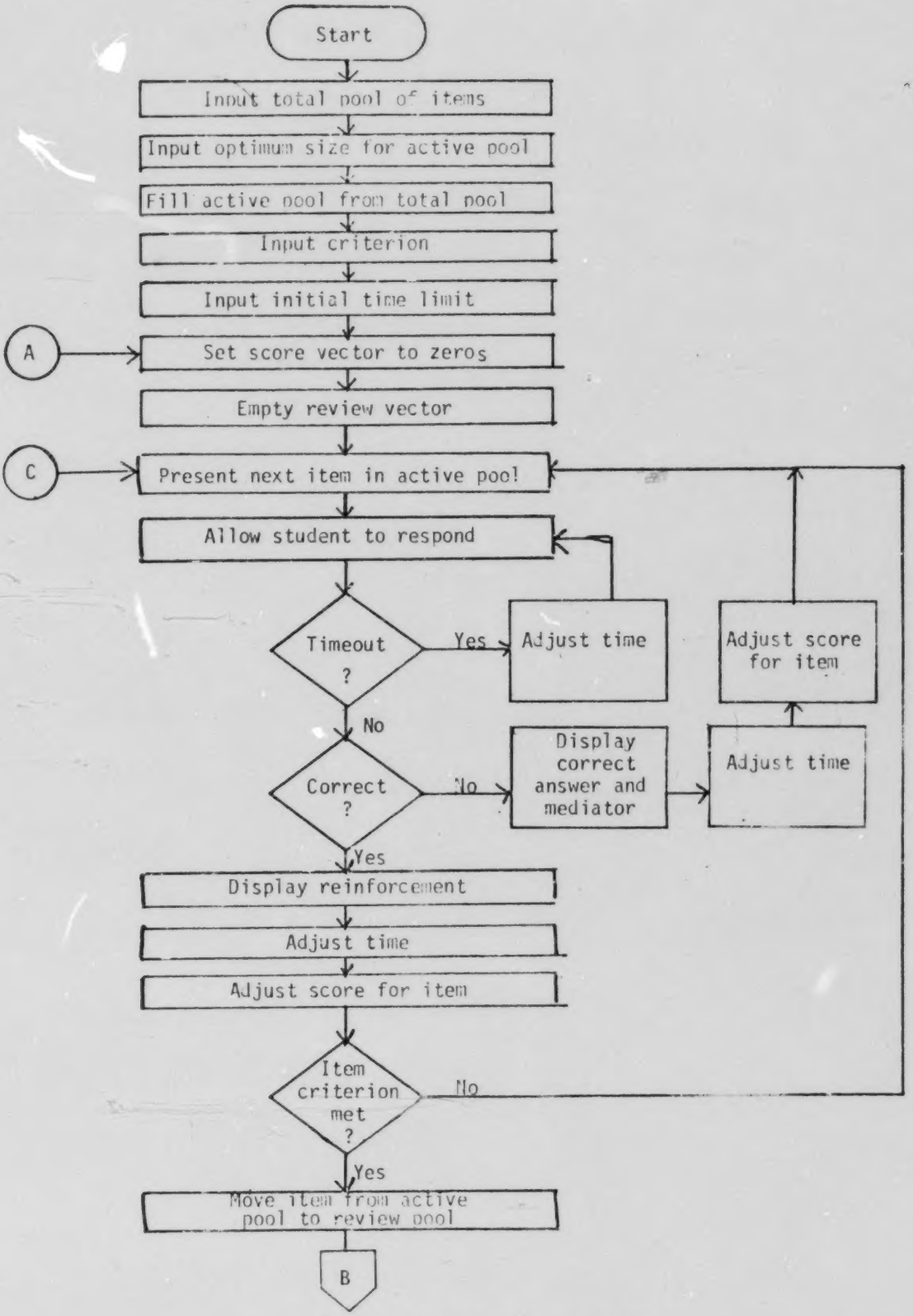


Fig. 5. Domain-Exhausting Model.

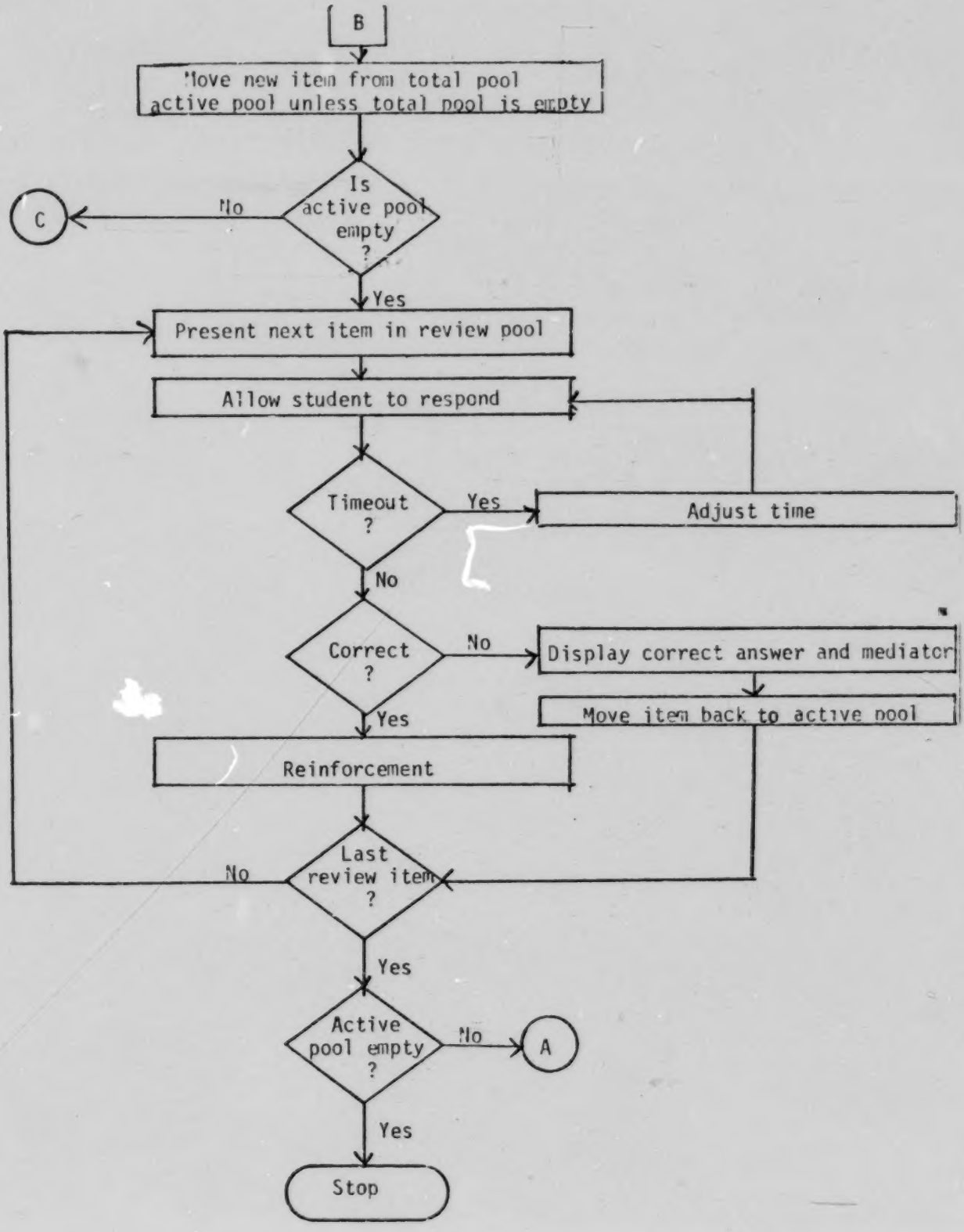


Fig. 5. Domain-Exhausting Model (Continued).

According to Suppes (1964), the optimum block size depends upon the relationship between rates of learning and forgetting. When learning occurs faster than forgetting, it is possible to show that block size should be as large as possible. On the other hand, when learning is slower than forgetting, the block size should be small. Indices of learning and forgetting rates would, therefore, be desirable input variables for this decision process.

With regard to item sequence, there is evidence that practice in specific items should be distributed throughout the drill rather than occur in close succession (Fishman *et al.*, 1967). Thus, once an item has been mastered and, consequently, deleted from the active item pool, it shoud reappear occasionally for review purposes. The criteria for deleting an item from the active pool and the amount of review needed must be empirically determined. As with the domain-sampling model, it may be more efficient to give the student control over the amount of practice and allow him to request review items. Some early research in drill-and-practice (Repp, 1935) emphasized the benefits of isolated drill (a homogeneous set of items for one specific task) following the introduction of a new topic or for remedial work. However, a mixed drill; *i.e.*, one containing several types of items, is best for maintaining skills.

The difficulty of items may be based on structural variables as in the domain-sampling model. In a domain-exhausting model, the items are predetermined and not composed within the drill. Thus, indices of item difficulty could also be predetermined on the basis of previous administrations and used as input parameters to the drill. The ultimate adaptive model would dynamically update this index each time a student responds to the item. Item difficulty is also the basis for selecting the appropriate drill-and-practice model, *i.e.*, domain-sampling or domain-exhausting. If the items for the domain-sampling model are to be randomly composed, then item forms must be specified. If the items are to be sampled from a larger pool, in the case of the domain-exhausting model, the total list of items must be provided. The learning-and-forgetting curves for this type of task should be indicated to determine the optimal block size of the active pool.

If item difficulty is to be manipulated within the model, then the selection of appropriate structural variables for determining difficulty indices is, of course, dependent upon characteristics of the task. For vertical addition, these might include digit size and the number of rows (Woods & Hartly, 1971). For spelling words, length and troublesome letter combinations (*e.g.*, ie-ei) are among the structural variables influencing the difficulty of an item (Cohen, *et al.* 1971). A total of 24 structural variables for logical problems has been identified (Maloney, 1972). These range from number of characters to depth of embedding. From these few examples, it is evidenced that, while there are some common factors; *e.g.*, size of problem and difficulty of specific elements, the identification of specific structural variables will be unique to each task with some expectation of carryover to similar tasks within a class.

Decisions regarding individual frame characteristics are the same for both the domain-sampling and the domain-exhausting model. First, a choice must be made among alternative media such as teletype. CRT, image projectors, and audio devices. The nature of the task may restrict this selection some. If there is still a choice, it could be based on the input variables describing student characteristics.

There are also many options for determing the time to allow for responding to each frame. These range from no limit at all to a time limit dynamically adjusted to challenge each student, *i.e.*, pacing. The time limit for a particular task may be fixed for all students or predetermined for each student on the basis of input variables. If speed is a critical element of the task criterion, then perhaps it could be specified as a goal, and feedback on response latency could be provided to inform the student of his progress toward this goal.

Another frame characteristic is the means by which the student will respond. For multiple choice items, he may respond via light pen or typing a character from the keyboard. In adition to typing a word or phrase for a constructed response question, one can imagine items in which the student indicates parts in a schematic with a light pen.

With regard to feedback, it has already been mentioned that response latency would be useful information to give the students in special situations. The more common varieties of feedback inform the student of the quality of his response. In addition to telling the student if his response is correct, it is sometimes possible to provide diagnostic feedback indicating the nature of any errors. A common strategy is to provide prompts or hints when a student makes a mistake and require him to answer again (overt correction).

The criterion of acceptable performance is directly related to the nature of the task. For some tasks, speed is a crucial element and assumes a more dominant role in determining the student's success or failure for a particular item. In such a situation, the student may be given a speed goal and updated information on his response latency. When he consistently responds correctly within the item limit specified by the goal, then he has met the criterion. The items in such a situation are usually of very low difficulty. Most tasks place more emphasis on accuracy and would, therefore, specify a criterion in terms of proportion correct. For some tasks, however, the consistency of correctly responding would be a better indicator of mastery. This would include concept identification and discrimination tasks in which the student will always answer correctly once he has learned the concept. The criterion of acceptable performance must, therefore, be specified for each task on the basis of the goal for the task and the evidence needed to judge if the student has reached the goal.

Output. The essential to be determined is the number of items to present to the student during drill-and-practice. Since different students require a varying amount of practice, it would seem most efficient to attempt to adapt the amount of practice to the individual. Thus, students are not wasting time with unnecessary practice and, at the same time, they are receiving enough practice to achieve the criterion. Several strategies will be employed to determine the number of items the student should be presented in the drill-and-practice sequence.

- The simplest model prescribes a fixed number of items for every student. At the end of the sequence, the percent correct is determined to predict mastery or nonmastery.
- A second method predicts mastery when a student has given a specified number of consecutive correct answers. Such a model would be appropriate for concept-learning in which the student will always answer correctly once he has mastered the given concept. According to Gagne (personal communication), one correct answer is sufficient to indicate that the student has mastered a rule. However, he also specified that students should be given additional practice in later review sessions.
- A more elegant decision mechanism employs statistical techniques such as Wald's Sequential Probability Ratio (1950) test, which uses students' performances on items to predict mastery or nonmastery. The number of items presented depends upon the student's performance on each item.
- An analysis of student response latencies will also be useful for predicting mastery. Theoretically, the initial latencies would be relatively high with the curve decreasing until it reaches some asymptotic level at which mastery can be predicted. This model, however, must either make the assumption that all items are of equivalent difficulty or include in the decision process some means of accounting for variations in item difficulty.
- Another means of deciding when to terminate a drill may be to allow the student to judge if he has reached mastery. In other words, this model would give the learner control of the amount of practice for a drill sequence.

There is no evidence to show that one of these methods would be more efficient than another. One must always be aware of the tendency to be swayed by the more elegant adaptive mechanisms when, in fact, a less intricate strategy might be just as efficient.

Recommendations

- From the preceding discussion, it should be evident that there are many decision points within a drill-and-practice model. Currently, most of these decisions will need both conceptual and empirical exploration. It is recommended that these variations be incorporated in the AIS research plan.
- On the basis of the literature review, it is recommended that two simulations of adaptive drill-and-practice models be developed. The first would involve the performance contingent-pacing paradigm and the second would involve an adaptive decision-making mechanism to terminate the drill when it is possible to predict mastery or nonmastery.

- For each review session, a drill-and-practice model should be utilized to formulate the problem list, organize the sequence, and provide optimal allocation of practice per problem type. All instructional decisions should be based on individually determined parameters.

More specifically for the AIS project, the drill-and-practice model should be utilized in the courses as follows:

- For Inventory Management, the focus should be on coding/index schemes and classification structures as in security rules;
- For Precision Measurement Equipment, the major emphasis should be on technical and conceptual aspects of the course; and
- For Weapons Mechanics, the focus should be on conceptual factors of electricity and image/photo requirements of specific weapons.

IV. SIMPLE CONCEPT ACQUISITION MODELS

Characteristics of Adaptive Concept Acquisition Models

Adaptive concept acquisition (ACA) models are represented by instructional paradigms designed according to decision processes that adjust instructional variables to individual differences and differential learning performance. For the adaptive concept acquisition models, the basic variations proposed are of two functional classes--pretask and within-task variables. Pretask variables are composed of individual difference and task variables, such as ability and problem difficulty. These variables serve to set limits on the instructional alternatives available, and the media to be used for instruction. In the second class, within-task variables provide for the manipulating of such alternatives as the number of examples, the degree of prompting, and the nature of the feedback/correctional process based on individual criteria. Thus, the flexibility of the ACA models are distinguished by the varying levels of adaptability. In the AIS context, this means that the model can be modified to reflect the diversity of concepts being taught. This is an important consideration in that the complexities of the targeted concepts should determine the degree of adaptability to individual differences.

Role in AIS

The adaptive concept acquisition models will probably play a fundamental pervasive role within AIS. While the current ATC instructional paradigm consists of lecture, small group demonstrations, individual practice, and criterion performance evaluation, the individualized concept acquisition instruction may replace lecture and small group demonstrations. As each lesson presents new concepts or reviews and combines previously introduced concepts, the individualized media assignment, examples, prompts, and feedback should facilitate the adaptive process. For the purpose of this report, the primary emphasis will be given to the optimal selection of the type and number of examples during concept acquisition.

Payoff of the ACA Models

As proposed, the ACA models may become an integral part of the computer-based and conventional media approaches to concept presentation and review. Given this high frequency of utilization, the models should provide for significant savings in training time and improved concept retention. As operational features, the following benefits of the application of the ACA models are envisioned:

- The pretask variables of ACA models are adaptable to individual student trait characteristics. Premeasured conditions would assist in the assignment of students to appropriate entry points within the instructional tasks. Such decisions would provide for residual savings in training costs by allowing high-aptitude students to finish courses more rapidly, or to receive enrichment training. Individualized assignment of low-aptitude persons to appropriate instruction has been shown to increase efficiency.

- The within-task variables are designed to select instructional materials based on a student's state characteristics. In a concentrated learning environment, individual performances fluctuate so that premeasures do not always indicate accurate assessments of current capabilities. These within-task variables make the presentation self-modifying in that it is continuously being adapted to the student's current response pattern and state levels.
- Since the ACA model will be computer-based, each student will have immediate access to adaptive instructional materials.
- Instructional theory concerning media, feedback, knowledge of results, sequencing, role of examples, and type of display can be designed into the adaptive individualized packages.
- The utilization of ACA models should improve cost-effectiveness by providing a more precise prediction of the necessary media and materials overlap than is currently available.

Literature Review for Conceptual Acquisition Model(s)

Instruction is a process of manipulating the environment to produce a desired change in a student's behavior. The goal of AIS is to implement an instructional system that will take into account individual differences so as to increase the effectiveness and efficiency of student learning. Early attempts to solve the problem of individual differences have been suggested and developed with varying degrees of success. One widely used practice was grouping or tracking of students by grades, or by scores on ability tests as an attempt to take into account individual differences. This homogeneous grouping had little effect because the groups seldom received different kinds of instruction. Air Force training incorporated Skinner's (1958) linear programmed instruction, which allowed students to progress at their own rates. This procedure emphasized that individuals do function at different learning rates; however, the material itself was not individualized since all students received the same instructional sequence. The influx of technology influenced Crowder's (1959) procedures of intrinsic programming with provisions for branching able students through the same material more rapidly than slower students, who received remedial frames whenever a question was missed. This type of programmed instruction was not widely used in Air Force instructional situations, or in any other institution, because of the difficult developmental task which required review sections for each alternative answer.

There are two basic procedures for designing concept acquisition instruction, which would have adaptive capabilities extending from the above assumptions. The first involves the use of premeasure(s) (such multiple variables as aptitudes, personality variables, and anxiety) for diagnosing the student's behavior and then prescribing a specific learning task designed to adapt to these individual differences. The second applies intermediate evaluations of the student's progress within the instructional sequence and assigns adaptive segments to correct errors in acquisition.

Pretask Adaptation

Cronbach (1967) discussed the applicability of adaptive instruction to student differences by suggesting that, if development in a wide range of persons was to be facilitated, a wide range of environments suited to the optimal development of each individual must be offered. In terms of AIS, this would mean having instructional units covering content available in different formats or sequences which can be adapted to differences among students. For example, Cronbach's model might prescribe one type of sequence and media for a student of certain characteristics, while another student of differing characteristics would receive an entirely different mode of instruction. The advantage of the ACA model over other computer-based decision programs would be the flexibility of selecting decision conditions which would change according to concept content.

In order to identify methods of prescribing optimal instructional strategies, Cronbach (1967) advocates that an extensive research program be conducted to identify those aptitudes which intereact maximally with instructional treatments. This body of research has become known as aptitude treatment interactions (ATI). Implicit in Cronbach's model is the assumption that specific instructional treatment assignments can be made from empirically determined measures existing prior to the onset of instruction. A further assumption is that a regression model could be developed for the assignment of individuals to different instructional strategies.

Recent research studies (Tallmadge, Schearer, & Greenberg, 1968; Cronbach & Snow's review, 1969; Dunham and Bunderson, 1969; P.F. Merrill, 1970) have investigated the assumption to determine if premeasured individual aptitudes interact with instructional treatment. These studies indicate that disordinal interactions of ATI's have an elusive nature. Bunderson and Dunham (1970), in the final report of a 3-year research project on cognitive abilities and learning, challenged the ATI concept as a viable predictive procedure in "real world" instructional contexts. The reasons for their skepticism can be summarized as: (1) the rarity of useful disordinal interactions; (2) disordinal interactions are not sufficiently robust after minor changes in the task or population; (3) the benefit from disordinal interactions may be less than that attainable through revision of a single optimal treatment. In this report, Bunderson and Dunham (1970) suggest that, instead of seeking disordinal interactions in order to assign individuals to different macro-treatments, ATI's be used to revise the optimal treatment to reduce the learning burden of slow-aptitude individuals. After the effectiveness of the single best treatment has been maximized using a systematic approach to instructional design (Bunderson, 1970; Tennyson and Boutwell, 1971), macro-treatment variables can be applied adaptively in the instructional program rather than produce entirely different alternative treatments. For developmental concerns of the AIS, this would mean designing an optimal concept acquisition instructional program, using the most efficient sequence, the most appropriate media for display, and the most effective instructional examples. Adaption within the program would then occur when students deviated from the optimal program.

Within-Task Adaptation

The second procedure proposes adapting instructional strategy according to a student's behavior in the learning program, and to other current state characteristics. The within-task adaptation procedure can be contrasted to Cronbach's approach in that individuals are *not* assigned to different macro treatments, nor are measures obtained prior to the entry of the individual into the instructional task employed. On the other hand, the within-task procedure differs from Crowder's approach in that Crowder utilizes only the last response made by the student in reaching an instruction decision. The within-task adaptive strategy would make instructional decisions based on an updated history of the student's behavior during a segment of the concept-learning tasks. Furthermore, the reliability of a pattern of responses compared to a single response should increase the validity of such adaptive decisions. In AIS, decisions on media and mode of instruction for particular units would depend on what is the most appropriate method of presentation. When student's deviate from the optimal sequence, they can be assigned corrective instruction. The within-task method of adaptation is such that remedial "hole patching" (Cronbach, 1967) is avoided on the basis of instructional theory and can be validated empirically.

There is research evidence (O'Neil, Hansen, & Spielberger, 1969; Leherissey, O'Neil, & Hansen, 1971; Tennyson & Woolley, 1971; P. F. Merrill & Towle, 1971) that trait or state variables measured prior to a learning task are not as effective in predicting student performance as state variables measured during the actual learning of the task. These findings suggest that it would be possible to include such measures during the task to adapt instructional sequencing for those students at the extremes on these measures.

The within-task adaptation model is based on three basic assumptions: (1) there are a limited number of different kinds of behavior or types of learning (Gagne, 1970; M. D. Merrill, 1971); (2) there is an optimal group instructional strategy or paradigm based on the conditions of learning for each behavior level; and (3) individual performance can be optimized by making adaptations to the group instructional paradigm according to individual response patterns.

Concept Acquisition

Mechner (1965) defined concept acquisition as the process of generalizing within a class and discriminating between classes. For example, in the Weapons Mechanic AIS course, students would have to identify certain types of wiring systems, and at the same time, discriminate between the systems. To teach this skill, Markle and Tiemann (1969) and M. D. Merrill (1971) postulated that concept acquisitions would result if examples during instruction differed in the irrelevant attributes associated with each; that is, each kind of wire should be system presented in many different colors, thicknesses, structures, etc. Such presentation promotes generalization within the class. Discrimination between classes is facilitated by presenting nonexamples which have irrelevant attributes resembling those with given examples; for the wiring illustration, the various wiring systems would be nonexamples for the one system under instruction.

In testing for concept acquisition, it is vital that the items on the test must be new, not used in prior instruction. A good set of items must have a number of other characteristics. In order to test for generalization across the total range of examples included in the concept, test items must cover the range specified by a thorough analysis of the concept. The number of examples the student can correctly classify is less important than the range of examples to which he can generalize. Discrimination of nonexamples can also be tested when the analysis of the concept has identified the key relevant attributes.

Tennyson, Woolley, and Merrill (1972) designed an optimal group instructional strategy for teaching concepts based on the theoretical work of Markle and Tiemann (1969, 1970), Merrill (1971), and Woolley and Tennyson (1972). The concept that Tennyson *et al.*, chose to teach was the metrical concept, "trochaic meter," as exemplified in poetry selections. As a preliminary estimate of range, they asked students unfamiliar with poetry to classify a large number of examples and nonexamples of the concept on the basis of a given definition. Some obvious examples were recognized by almost all subjects and were, therefore, termed high-probability examples. Some nonexamples were equally obvious and were termed high-probability nonexamples. Examples which were difficult to recognize were termed low-probability examples; subtle discriminations which could not easily be made on the basis of the given definition produced low-probability nonexamples. Thus, both range of examples and fine discrimination of nonexamples were defined in their study on the basis of ratings by representative subjects rather than on a prior analysis of the concept.

Tennyson, Woolley, and Merrill (1972) hypothesized that different combinations of these high- and low-probability examples and nonexamples would produce predictable errors in concept acquisition. Markle and Tiemann (1970) had proposed that restricting the range of examples would cause a student to undergeneralize, that is, to accept on a test only the same limited range provided in instruction. Tennyson *et al.*, produced precisely this effect by giving students instruction which included the definition, only high-probability examples, and the subtle discriminations taught by the low-probability nonexamples. They also proposed that poor selection of nonexamples, in conjunction with a broad range of examples, would cause students to overgeneralize and to accept nonexamples as members of the class on a test. This effect was produced by providing instruction including the definition and full range of high- and low-probability examples but only very high-probability nonexamples. In other words, no difficult discriminations were taught, and, on the test, these students did not succeed in making such fine discriminations.

In their study, they also demonstrated the effect of a particular kind of limitation on the range of examples, in which one salient but irrelevant attribute is always present. The attribute used was Victorian origin of the selections. All examples of trochaic meter given students in this treatment were dated in the Victorian period, while nonexamples were selected from earlier or later periods. Despite the definition directing attention to the meter of the examples as the critical attribute, students showed a misconception on the test, that is, they generalized correctly only to examples of trochaic meter written in the Victorian period. They rejected true examples from other stylistic eras and accepted some Victorian nonexamples.

Tennyson, Woolley, and Merrill's data support the position that the selection of both examples and nonexamples is an important item in effective concept teaching. A wide range of examples prevents undergeneralization, while a good selection of nonexamples prevents overgeneralization. In AIS developmental projects, the Tennyson *et al.*, model has application to the actual design of the ACA instructional materials. The system provides a method for selecting instances and sequencing them to an optimal task. The component variables are uniquely adaptable to individual characteristics. Thus, they have the capabilities for within-task adaptation, for example, if a student is committing a certain kind of classification error on an intermediate evaluation, the type and degree of examples and nonexamples can be adjusted to correct the error. The model also allows for designing a multiple-entry program based on pretask measures. Students with poor reading ability, for example, would enter the task with easier high-probability instances than someone with good reading ability.

Applications of CAI Concept Acquisition

A number of CAI applications using various types of adaptation have been implemented with a good degree of success. A number of them are reviewed in this section. The first application uses the Tennyson *et al.*, concept acquisition paradigm in individualized CAI programs. The other projects offer a summarized review of the feasibility of computer-controlled adaptive instructional models. The review also introduces other adaptive characteristics that can be included in the ACA model.

Brigham Young University-TICCIT. TICCIT is an instructional development project which is undergoing continued development at Brigham Young University. The project consists of developing CAI courses in the areas of mathematics, English composition, and both remedial English and mathematics. The instructional materials are being developed according to the research paradigms developed in the Tennyson, Woolley, and Merrill investigation.

The objectives of the project encompass both cognitive and affective outcomes. These are, first, that students will achieve mastery at any of three levels of sophistication (the students contract individually for a desired level). The second objective is that students will develop a more positive attitude toward the subject matter. Third, students will develop improved strategies for learning. Finally, students will develop a sense of responsibility for their own learning. It is planned to achieve these objectives by three main approaches: (1) control structures, which provide for learner control, (2) the construction of a high-level "advisor program," and (3) the use of a variety of motivational techniques.

The control structures provide for full learner control of instruction, which is expected to encourage approach responses to the subject matter, enhance learning strategies, and develop the student's responsbility for his own learning. Within each unit of a course, the student will be able to select from a "menu," giving aspects of the unit he wants to see and the sequence in which he wants to see them. A typical menu includes the following:

- The objectives of the unit which give an indication of the structure of the lesson
- Review tips, which discuss the prerequisites for the lesson and provide brief review material
- A "so what?" section, which tells the student why he should bother to learn the lesson
- A mini-lesson, which is a quick survey of the entire lesson
- A definition section in which the major concepts involved in the lesson are defined
- The instructional section, which provides structured instruction (the content of the lesson) and teaches the algorithms for performing the skills involved in the objectives. It is within this section that the main features of the teaching paradigm described in this paper are employed.
- The mastery test, which diagnoses the student's degree of success or failure.

The advisor program used within the project may be called by the student at any time for advice regarding the best strategy to adopt for a particular lesson. The student can also request a status report to see what lessons he has completed. He may further ask if, judging by his achievement profile, he could take additional options which will enhance his grade. The advisor program is also used to "advertise" certain "fun options" which are included in the course for motivational purposes.

Motivational techniques being developed in the project include the "so what?" section in each lesson, the fun options, and a point system used to earn these fun options. The fun options are made available to the student contingent upon his success on the mastery test of a given lesson. They include such items as "more on the topic," a computational plotting program (for the math course), games, short films, and tidbits such as historical vignettes, anecdotes, etc. related to the lesson.

In summary then, the control structures permit the student to adapt instruction to his own particular needs, while the advisor program provides the student with the pertinent information needed for him to adapt the instruction successfully. The motivational techniques, finally, provide the incentives which will help him optimize his learning. Specific adaptation within each lesson is also provided in the instruction part of the unit, where the concept-teaching paradigm elaborated in this report is employed.

Stanford Project. At Stanford University, Friend and Atkinson (1971) developed a course entitled "Introduction to Programming" for use by NASA personnel. The course consists of a set of 50 lessons, each about 1 hour in duration. The course teaches programming concepts through a simple computer language called AID, and makes a provision for student practice through a number of exercises designed to help the student solve simple programming problems. These lessons are tutorial in nature, that is, no previous knowledge of computers or programming is necessary. The branching logic used in problems permits five discriminations between student responses, thus greatly refining the remediation process. That is, not only

may a response be diagnosed as "correct" or "incorrect," but degrees of correctness can be established for a given problem. This response analysis is made by means of twelve basic analysis routines which can return different values of correctness, thereby refining the remedial feedback to the student.

In addition to this implict branching, the student can also initiate branching by requesting additional information through the use of HINT and TELL commands. When the student encounters some difficulty in solving a problem, he may thus request a hint which will set him on the right track. Currently, two hints are available for most problems and as many as six are provided for particularly difficult problems. The TELL command, on the other hand, will cause the system to print the correct answer to a problem on which the student is really stuck.

A further optimization scheme is available. In this plan, the response of a student determine the number of problems that constitute a lesson. In a given lesson for example, one student may do 30 problems, while another may do as many as 70. Specifically, the number of problems presented is governed by a simple heuristic which will cause the student to bypass all subproblems related to a top-level problem which is correctly answered. Through these decision processes and the strong provision for student control, the system allows the better prepared and more able students to keep up a fast pace while at the same time enabling the less able students to progress at their own rate, thus, making use of additional and remedial information.

Fort Monmouth Army Project. A major tutorial CAI application was developed by the Army (Grunti & Longo, 1971) at the Fort Monmouth Army Signal School. The instructional model utilized in the course specifies a single-track teaching sequence. However, individualization is accomplished by dividing the trainees into high-, middle-, and low-aptitude categories. Each category is then treated differently. Each lesson includes a pretest, but only the high- and middle-aptitude students are permitted to take it and skip ahead if they reach criterion. Experience with the course has shown that the probability of passing the pretest is much greater for these trainees than for the low-aptitude trainees. The high-aptitude trainees with superior learning ability are also permitted to take instruction in larger increments than middle- or low-aptitude trainees. In all cases, remediation follows incorrect responses to the program, whereas correct responses are always confirmed, or reinforced before the trainee continues through the course. The decisional model, therefore, has many fewer individualizing options than the Stanford model, but it does capitalize on rate of progress through the course.

Other CAI Applications. A number of other CAI installations, mostly university-based, have also implemented a variety of adaptive applications. At Florida State University, for example (Hansen, Dick, & Lippert, 1969), a CAI physics course was developed which incorporated individual reading, computer quizzes, audio lectures, single-concept film loops, and films. The flow from one medium to the next, as well as general progress within the course, was governed by the student's achievement on the computer quizzes. Results of a comparison with the traditional lecture method indicated, in the first field study, that the CAI students were significantly better on the final grade assignment than the students in the conventional method. A time savings of 17 percent was also effected and, while the conventional course achievement was marked by a gradual decrease in performance as the physics topics increased in complexity, achievement in the CAI conceptual problem exercises was markedly constant.

At the University of Texas at Austin, a number of short courses have been developed. These courses range from the hard sciences (chemistry, mathematics) to the humanities (music, Arabic). A similar situation exists in public education utilizing CAI. The CAI Laboratory of the Kansas City Public School District, for example, provides adaptive instruction in areas such as scientific notation, mathematics, biology, and pollution.

Model Structure

The ACA instructional system incorporates standard individualization components of learning rate, self-pacing, providing on-line and off-line assistance, flexible utilization by the trainee, remedial capabilities, review frames, enrichment material, and behavioral modification variables such as incentives, praise, and motivation. The two basic functional classes of the ACA models, pretask variables (set limits on the instructional alternatives) and within-task variables (modifiable alternatives), can be designed into two adaptive concept sequences--a general adaptive model and a specific adaptive model.

Concept Adaptive Sequences. As discussed in the literature review section of this report, the within-task adaptation provides an accurate assessment of the student's performance in a given program of instruction. An optimal instructional task is presented to the student, and upon completion of the initial segment, the student is tested. The test performance is evaluated in relation to the three types of classification error (overgeneralization, undergeneralization, and misconception). If he has no errors, that is, he reaches criterion, then he continues the unit's instructional sequence. However, if he does not make criterion, his responses, both right and wrong, are analyzed to determine the type of error being committed.

General Adaptive Model. The first adaptive concept sequence, termed general adaptive, prescribes a predesigned instructional program which follows the results of the initial test to determine if the student is committing a classification error. This model regulates the student's instructional sequence as he progresses toward the terminal objective of a given unit of instruction. After the initial evaluation, each student's sequence of instruction is modified according to individual response patterns. For example, students who overgeneralize on the beginning segment of the task would be presented higher probability instances with increased prompting. The number of intermediate evaluations is determined by the concept difficulty. Some concepts may use only one sequence of examples followed by an exam, which would provide remedial help for those with errors. Another unit might involve teaching several complex concepts, requiring several intermediate tests and remedial frames.

Specific Adaptive Model. The second functional class of the ACA models is utilized in the specific adaptive model. The student would receive at the beginning of the instructional unit a presentation presumed to be optimal, followed by a intermediate evaluation. The within-task variables would be adjusted according to degree and type of classification error the student is making at this point. Degree refers to the measured severity of the error, that is, learners differ in the magnitude of incorrect responses. Whereas in the general model, the student would be given a predesigned task to correct the error, the specific model would select a unique series of examples, in terms of difficulty and number of examples to correct the error. Thus, if a student was only making a slight overgeneralization, his remedial instruction would use only a few examples, while a student making a gross overgeneralization would receive a large number of examples. In each case, the decision parameters would ajust to the type and degree of error.

Program Sequence Selection. In the various courses taught in the AIS, concepts vary in terms of complexity. In cases where concepts are difficult, it is desirable to design units with multiple entry points. In such situations, pretask measures could be used to start the instructional presentation at a level of difficulty which is appropriate to an individual airman. For complex concepts omitting a pretask measure to flag appropriate entry points into the program, optimization would be limited to the use of remedial frames to correct errors. The pretask measure allows low-aptitude or highly anxious students to enter a given program at a point which provides more instructional examples than a high-aptitude student. Thus, both pre- and within-task adaptations are necessary in complex concepts. On the other hand, the sole use of the pretask measure, would offer only a gross adaptation to the student's characteristics. While the pretask procedure adapts the presentation to the student's entering trait capabilities, the within-task procedure makes the presentation self-modifying since it is continuously being adapted to the student's current response pattern and state levels.

Interaction of Task and Student Characteristics. The pretask adaptive decision process which operates to enter a student into the unit of instruction for a complex concept at his optimal level is based mainly on an accurate evaluation of whether or not the student has in his repertoire the prerequisites to the unit. Although preskill evaluation remains the most important component of the decision process, other variables also play a part in optimizing entry to the unit. Among these variables are aptitude indices (*e.g.*, AQE), personological characteristics (*e.g.*, anxiety and curiosity), and cognitive styles.

Once the student has entered the unit at his optimal level, these characteristics will interact on a frame-by-frame level with task variables to produce a given net amount of learning; or, at intermediate levels, to produce a set state of progress. In order to optimize this progress, therefore, the instruction must adapt to this interaction between task and student characteristics. This interaction can be continuously monitored by the computer through an appropriate analysis of the student's cumulative response record. The basis then for the specific adaptive decision process lies in a correct classification of the student's successes and difficulties as they are evidenced over time within the unit. Only if the decision rules effectively deal with this aspect of the process will prescriptive measures (including both remediation and

enrichment be appropriate to an optimal progression through the unit. These decision rules may involve multiple factors, such as degree of correctness of the response, response latency, and cumulative indices of these two and other possible factors. The appropriate mix of factors which enter the decision rules will be, most probably, very heavily task-bound. That is, the optimal combinations will be different from task to task and will depend directly on the given task's specific characteristics. This optimization, or course, will evolve only through sustained formative evaluation of the decisional rules included in the model. In the meantime, however, a general, although less effective, approach can be taken. That is, broad decisional parameters can be established on the basis of the limited research evidence in instruction and theory.

Model Variables

A paradigm of instruction for concept acquisition was discussed by Gagne (1970) and empirically investigated by Tennyson, Woolley, and Merrill (1972). Concept acquisition was defined as the ability of the learner to correctly identify previously unencountered objects or events (or representations of such objects or events) as members or nonmembers of a particular concept class. It was assumed by Gagne (1970) and Tennyson (1972a) that for a given learning behavior, an optimal information processing strategy can be identified. By manipulating task variables such as stimulus similarity, prompting procedures, sequence, and difficulty, an optimal instructional strategy for concept-learning can be designed.

Instructional Model

The payoff of educational research is the application of the findings in an applied instructional environment. The purpose of this report is to demonstrate the feasibility of applying research variables on concept acquisition into a generalized adaptive instructional model for teaching concepts in the AIS system. This report does not present the methodology for the decision/selection stages in designing the actual instruction task; other sources give in-depth descriptions of those procedures (Tennyson, 1972a; 1972b). The purpose here is the presentation of the management model rather than the developmental procedures. The instructional model (Figure 6) is designed to accord with conclusions from research studies investigating those variables hypothesized to have a direct application to concept teaching. The instructional model's components are discussed in the following paragraphs:

(1) *Pretest*. The first component of the instructional model is a pretest on the concept class to be taught which assesses the student's entering behavior. The criterion referenced testing evaluates minimum capabilities. If the student meets criterion, he advances to Step (5), classification test; if not, he proceeds with Step (2), definition.

(2) *Definition*. In a study by Merrill and Tennyson (1972) on prompting effects, it was found that subjects performed significantly better on the learning task when given the definition which identified the relevant attributes of the concept class (Markle & Tiemann, 1972) without the definition. The definition is a statement identifying the relevant attributes shared by a set of instances in a given class. Relevant attributes are enabling or prerequisite concepts assumed to be known by the student. Writing the definition requires a thorough analysis of the concept, usually resulting in simplification and reconceptualization of the class.

(3) *Review*. Merrill and Tennyson (1972) included a treatment condition which presented the prerequisite subskills of the concept being taught. The results did not indicate that this variable was a significant factor in task performance. However, certain blocking schemes of the data showed that subjects with low pretest scores receiving a review did better on the posttest than similar subjects not receiving the review. The review component is, therefore, included as a student option. In computer-controlled courses, students with low-aptitude profiles could be advised to take the review. Whatever the mode control, the students should make the basic decision (see Bunderson, 1971, for a review on learner control) of whether or not to take the review.

(4) *Instructional task*. Tennyson, Woolley, and Merrill (1972) developed an optimal group instructional strategy for teaching concepts based on the theoretical work of Mechner (1965) and Markle and Tiemann (1969, 1970). For concept acquisition, an optimal information-processing strategy consisted of presenting examples and nonexamples to the student in such a way that the relevant attributes were clearly contrasted with irrelevant attributes. Task variables affecting learner processing of this information can be determined by four categories of

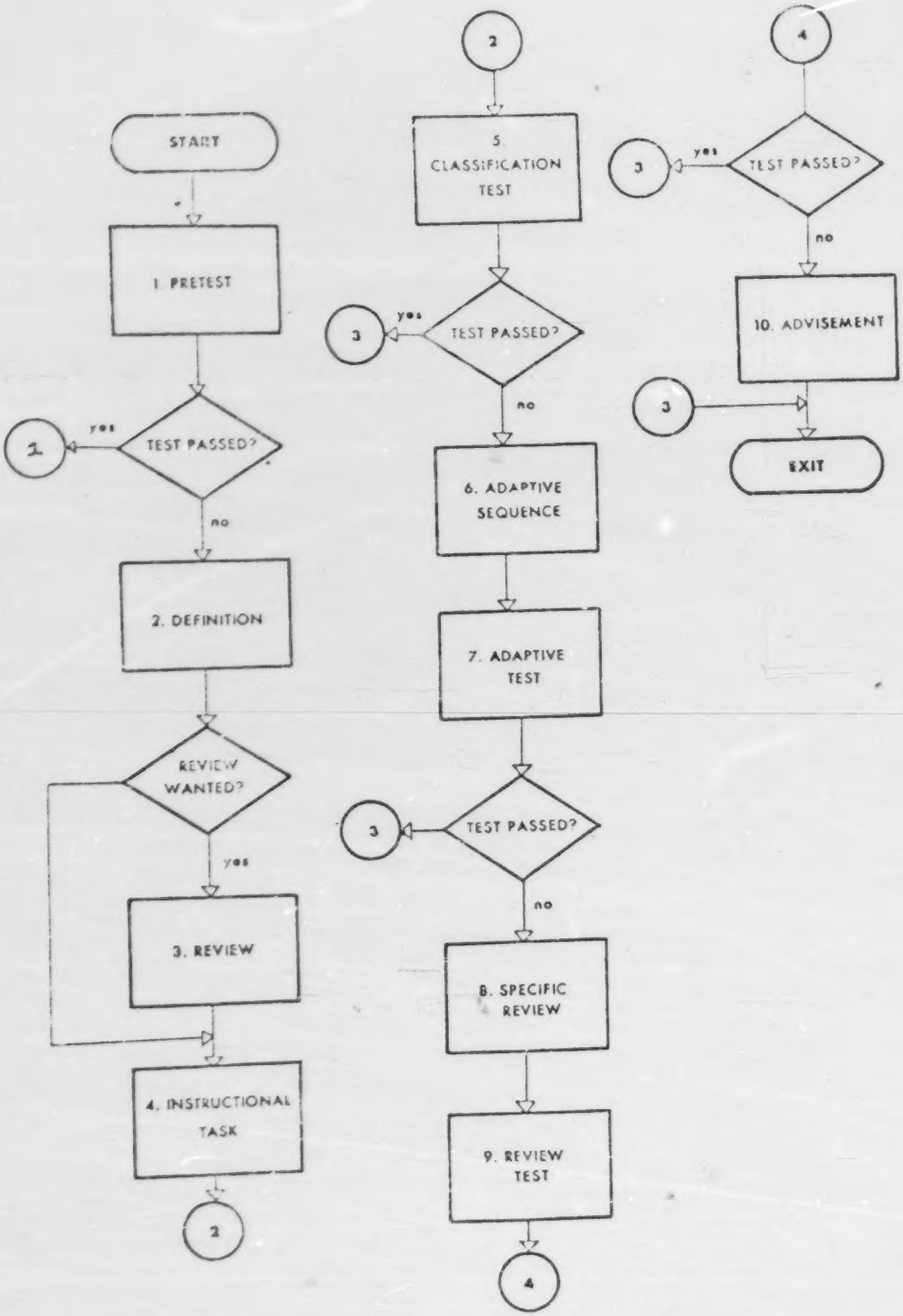


Fig. 6. Instructional Model for Concept Acquisition.

procedures. These categories are (1) stimulus similarity variables, (2) prompting/feedback variables, (3) sequence variables, and (4) instance difficulty. More detailed explanations of these items are as follows:

- *Stimulus similarity variables* include the following:
  - *Matching* of examples with nonexamples. An example is matched to a nonexample when both share identical or very similar irrelevant attributes.
  - *Divergent* examples. An example is divergent from another example when the corresponding irrelevant attributes are different. Examples which share the same irrelevant attributes are said to be convergent.
- *Prompting variables* include the following:
  - Presenting a definition which identifies the relevant attributes (Step 2 of the model).
  - Using various devices to identify the relevant attributes embedded in examples presented in the task.
  - Explaining why a nonexample is not an example.
- *Sequence variables* include the following:
  - Simultaneous presentation of instances.
  - Instructor-selected sequence.
- *Difficulty of instances.*

These four task variables are manipulated into an example set (Figure 7). According to the concept paradigm, two examples should be paired (divergent) so that they differ as much as possible in their irrelevant attributes. Within the same simultaneous presentation, two nonexamples are presented which are matched to their respective examples by having irrelevant attributes as similar as possible. This relationship of examples and nonexamples is designed to focus the student's attention on the relevant attributes. In the investigation by Tennyson (1972b) on the effect of nonexamples in acquisition, it was shown that subjects not receiving nonexamples responded randomly on the posttest, while subjects receiving nonexamples responded as hypothesized.

Prompting is used in the example sets to explain why an instance is an example or why it is not an example. The subject matter determines the type and amount of prompting necessary. Example sets range in difficulty from easy to hard. Depending on the adaptability of the program and the hardware, the instructional sequence could have multiple entry points and student control over exit. Entry could be determined by student profile data to individualize on trait and state variables.

(5) *Classification test*. Tennyson *et al.*, (1972) designed a posttest which was capable of detemining the degree and type of classification error the student was making at the conclusion of the instructional task. The test examined the subject's scoring patterns in four different ways to see if he made an overgeneralization, undergeneralization, or a misconception of the concept class (Markle & Tiemann, 1970). Construction of the classification test follows the same procedures as outline for the instructional task. The task presentation is expository, that is, the student is told if an instance is positive or negative. The classification test, however, is inquisitive, that is, the student is not told the nature of the instances. Although feedback is given on the correctness of the answer, no prompting is given a wrong answer. Students meeting criterion on this test are finished with the lesson, while students failing to pass the classification test proceed to the next component, where they receive remedial instruction based upon the type of classification error they made on the test.

(6) *Adaptive sequence*. Simple concepts would require only specific review if a subject fails the classification test. For complex concepts, it is possible to identify the type of student error if criterion is not met (Tennyson *et al.*, 1972; Tennyson, 1972a). The two basic levels of adaptation that are possible are (1) general and (2) specific. In the general adaptive sequence, students are classified into one of the three error categories. For each category, an optimal

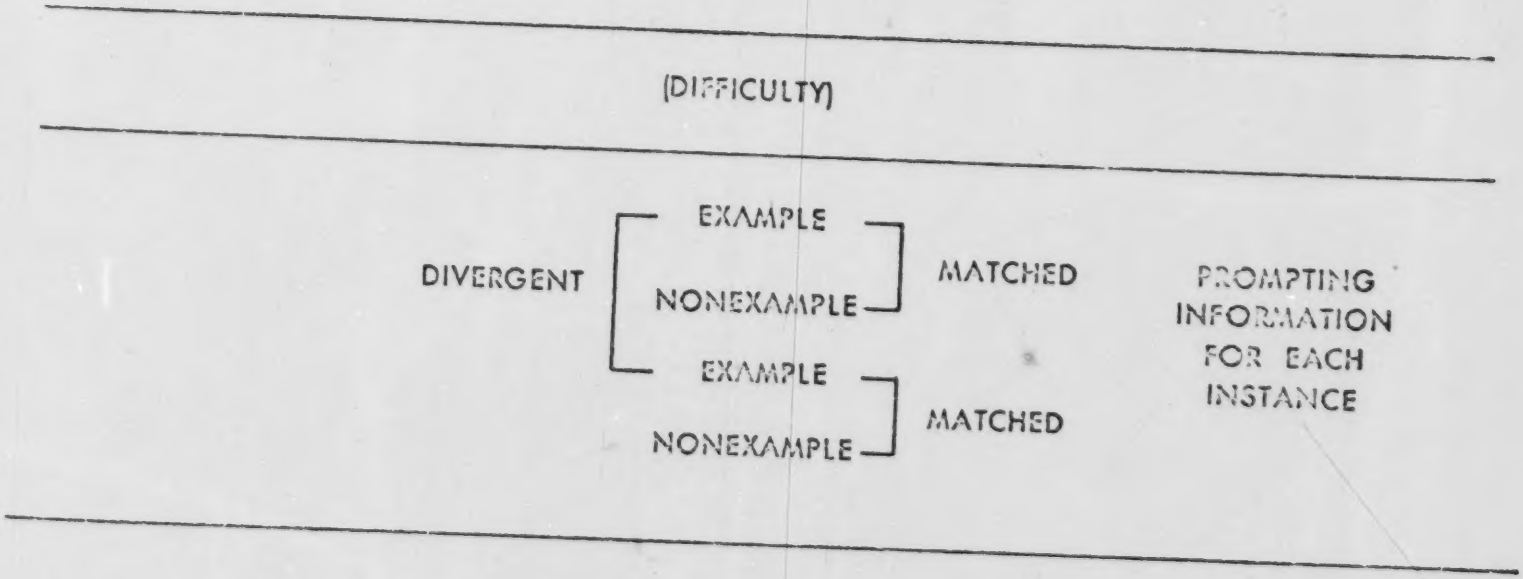


Fig. 7. Relationship of Examples and Nonexamples in Concept Acquisition.

group instructional task is given to correct the error. For example, if a student overgeneralizes, a specific program designed to correct that classification error would be given. The corrective programs would be as follows:

- *Overgeneralization*. For students who overgeneralize, the general adaptive procedure would be to select instances of easier difficulty than normally would be used in a standard example set sequence used in the instructional task. Also, an increased level of prompting is given for each instance.
- *Undergeneralization*. This error indicates that the student failed to identify difficult examples. To correct this, the example sets would begin with harder instances than used in the instructional task. The sequence would basically concentrate on difficult example sets.
- *Misconception*. Since the subject seems to be focusing on some irrelevant attribute, the divergency of the examples would be expanded so that common irrelevant attributes are practically eliminated.

In all three corrective programs the students with each error category would receive the same modified sequence.

Specific adaptation is similar to the general adaptive condition in that adaptation is made according to type of error, but the corrective procedures also are individualized according to the degree of error. The degree of error is determined by the number of errors of a given type. A student who makes numerous overgeneralization errors would be given easier instances than a student who only makes a few. The specific adaptive sequence also would increase prompting in a controlled situation so that no student is either overloaded or insufficiently instructed.

(7) *Adaptive test*. This test is designed to evaluate the effect of the corrective sequence. Test items would reflect the type of error to be corrected. It would not be a comprehensive test unless that degree of error was committed. Passing this test would exit the student from the program. Failing again, the student would receive one further level of remedial instruction.

(8) *Specific review*. This form of correction has a long history in the field of programmed instruction. Remediation is specific to the item missed. Again the problem's degree of difficulty determines the amount of corrective review. Concluding this component of instruction, a final test is given.

(9) *Review test*. A standardized test similar to the classification test is given. A student failing at this point indicates that he has learned almost nothing from the instructional task. In such a case, this review test again assesses his behavior to perform at criterion. If the student meets criterion, he exits; if not, a continuation in the course is decided.

(10) *Advisement*. In complex courses, it is possible that some students would have difficulty with certain concept lessons. In such situations, two decision can be made—the student drops the course or he continues with the next lesson and reschedules this lesson for a later date. The student's individual cumulative profile is a major factor in the decision process (Bunderson, 1971).

Selecting New Instances

In any adaptive situation, a large number of instructional instances need to be available for immediate usage. Also, revisions of the content once the system is in operation need consideration. The instructional program described allows for the storage of a large supply of examples and nonexamples from which to select corrective sequences. A subroutine program developed at the Univerity of Texas (Bunderson, 1971) generates new instances for a polyomial task, including a probability rating. King (1971) of Florida State University developed a program that rates difficulty of prose materials based on scales of readability. These two programs illustrate that introducing new material into the instructional system can be a component of the main program.

The instructional model for adaptive concept acquisition was designed according to theoretical assumptions supported by empirical research data. The model allows for flexibility and modification by the contractor developing courseware for application in the AIS educational system. Although the model specifies concept teaching, other types of behavior could use the same sequence, and probably a typical instructional lesson would include various types of behavior. In such situations, research-based variables are available to adjust the model. In instructional projects where various behaviors are used, this model might be a subunit or a larger management model. The premises here are that instructional design should be decided by theory as much as possible, and that design components should represent a parsimonious approach to development.

Recommendations

The following recommendations are made:

- First, it is recommended that the proposed ACA Model be simulated and ultimately field tested since it focuses on a primary requirement of training, namely, concept acquisition. In addition, the ACA Model includes the training processes of diagnostic testing, definitional learning, adaptive sequences of examples, and reviews.
- Further, the topics of adaptive prompting, feedback, and task performance-related concepts should be incorporated within the ACA Model or become correlated models. Each of these variables should be systematically pursued within the AIS research phase.
- The use of pretask measures (trait measures) should be extended and utilized so as to increase the training efficiencies.
- The most cost-effective use of media and instructional resources should become an operational component within the ACA Model approach.
- The ACA Model should be extensively employed within each of the three AIS courses, and appropriate evaluative comparisons should be made.

V. COMPLEX TUTORIAL MODEL: RULE–LEARNING AND PROBLEM–SOLVING

Characteristics of a Complex Learning Model

Much of the instruction presented in ATC courses concerns the acquisition of what Gagne (1970) has called intellectual skills. Probably the most common type of learning undertaken by an airman is the acquisition of principles or rules. After he learns the application of principles for a rule, his subsequent behavior may be governed by that rule. The use of such rules allows an individual to respond to an enormous variety of situations in a consistent and effective manner.

M.D. Merrill (1971) defines a rule as a "statement of relationship between two or more concept classes." A student must show the relationship between these classes in order to demonstrate that he has learned the rule. It is not sufficient for the student to merely memorize the verbal statement of the rule. According to Gagne (1970), a rule is learned if a student is able to respond to a class of stimulus situations with a class of performances, the latter being predictably related to the former by a class of relations. M. D. Merrill (1971) further states that the student should be able to show the relationship between the component concepts or classes in an unencountered situation in which the given rule is relevant. Rule-governed behavior or rule-application behavior can be thought of, in computer science terms, as the ability to perform a specified operation on incoming data from a specified class of inputs to produce a specific output from a class of outputs. The inputs may be thought of as the domain of the rule which consists of elements from the concept classes which compose the rule. The outputs may be considered as the range of the rule which is bounded by the operation and permissible inputs.

M.D. Merrill (1971) describes problem-solving as that behavior which occurs when the student is able to select relevant rules for an effective solution strategy when presented with an unencountered problem situation for which the rules are not specified. The problem situation is one in which the analysis of several rules and the synthesis of a strategy for solution is required. Gagne (1970) states that problem-solving can be viewed as a process by which the student discovers a combination of previously learned rules that can be applied to obtain a solution for a novel problem situation.

The higher the type of learning required to achieve a stated objective, the more complex the instruction becomes. To further complicate matters, an increasing number of interaction variables such as features of the subject matter, characteristics of the instructional process, and the student's characteristics combine to require quite sophisticated instructional models. In this chapter, the major emphasis will be on an adaptive model for teaching rules. It is anticipated that this model may be extended and adapted for application in the teaching of problem-solving skills. However, such an extension is not described here. The latter part of this chapter does contain several implementations of highly interactive instructional programs for teaching problem-solving behaviors in a training environment. These instructional programs for teaching problem-solving are not elaborated in great detail, but they are highly suggestive in terms of AIS application.

The adaptive instructional model for rule-learning under consideration in this chapter will utilize a combination of multiple-regression techniques and heuristic decision rules to select and sequence instructional components into an idiosyncratic instructional strategy for a given student. The instructional components will be maintained and stored in interrelated and cross-referenced component pools. The instructional components will be selected from the appropriate pool and sequenced into an initial instructional strategy by the regression model and decision rules. Task characteristics such as rule difficulty and example difficulty, and the student's profile of personological measures such as cognitive abilities and learning style will be utilized to predict and specify the initial instructional strategy. Additionally within-task performance measurements such as number of items correct and test item response latency will be collected. These measures will then be utilized by the regression model decision rules to update the instructional strategy as necessary.

The specification of instructional strategies for subsequent rules will be based on the student's performance under previous instructional strategies. It is anticipated that, through the use of this iterative cybernetic-adative procedure, an optimal instructional strategy of rule-learning for a given student will be approximated over a short series of rules. The model also incorporates a provision for supplementary remedial instruction for students who do not have the necessary prerequisite skills related to component concepts and lower order rules.

The following subsection describes the role of rules and problem-solving in AIS. The theoretical and experimental literature which support the model under consideration is presented in the succeeding subsection, while subsequenct subsections describe the model in greater detail. The instructional components and consequent instructional strategies are also described.

The Role of Complex Tutorial Models in AIS

A relatively major portion of each AIS course involves instruction in both rules and problem-solving. While much of the fundamental information of a course is conceptual or psychomotor in nature, the use of this information requires the application of rules and the solving of problems.

The selection and completion of appropriate forms, item accounting, computer usage, stock control, and equipment management in the Inventory Management Specialist course all require the learning of rules in order to complete defined tasks successfully. Further, as difficulties are encountered while completing tasks, students are required to apply sets of rules to solve the problem and to complete the job correctly.

The vast majority of the learning taking place in the Weapons Mechanic course is at the rule level. Once parts of weapons have been identified, defined sequences of activities are presented as rules for disassembling and assembling each piece of equipment. Rules are also used in the teaching of systems functioning and safety practices. Problem-solving is an essential feature of the troubleshooting activities which occur both in the electricity blocks, linkless feed system blocks, and weapons systems blocks on the major aircraft.

The Precision Measuring Equipment course is designed to develop the student's knowledge and understanding of the principles (rules) of measurement with an emphasis on precision and accuracy in their use. The students are taught to calibrate, troubleshoot, and repair approximately 200 items of precision measuring equipment. The troubleshooting phase of instruction is basically training in problem-solving.

It is, therefore, essential that the instructional paradigms developed for the AIM specifically consider the kinds of instruction that are best suited to the training of students in the learning and application of rules, and the solving of problems.

Literature Review

The review which follows describes the literature related to rule-learning and problem-solving and is divided into segments describing instructional strategies, task variables, and student characteristics.

Instructional Strategies or Paradigms. Gagne (1970) has described the conditions which he feels are required for learning rules. The first condition or prerequisite for learning a rule is a knowledge of the concepts which make up the rule. Knowledge of these concepts implies that the student must be able to identify or classify appropriately examples of the component concepts. The conditions required for rule-learning within the learning situation include:

- A statement of the general nature of the performance to be expected when the learning is completed
- A presentation of verbal instructions which would invoke recall of the component concepts
- A presentation of a verbal statement of the rule
- A presentation of a situation which requires the student to demonstrate or apply the rule.
- Reinforce correct application of the rule.

These conditions imply an instructional strategy or paradigm for teaching rule-governed behavior.

Evans, Homme, and Glaser (1962) have developed a Ruleg system for the construction of programmed learning sequences based on rules (ru's) and examples (eg's). *Rules* are defined as statements of some generality from which substitution instances or examples can be obtained. This may include such things as a definition, a mathematical formula, an empirical law, a hypothesis, or an axiom. An *example* is defined as a statement of some specificity which is derived from the more generalized rules. The Ruleg system also is made up of additional components which are defined below with their corresponding shorthand notation:

- $\widetilde{ru}$ An incomplete or partial rule which requires the student to respond by completing the rule
- $\widetilde{eg}$ An incomplete or partial example which requires the student to respond by completing the examples
- $\widetilde{\widetilde{ru}}$ A terminal situation where criterion behavior is required with minimum stimulus support, and the response is usually a statement of the rule
- $\widetilde{\widetilde{eg}}$ A terminal situation where criterion behavior is required with minimum stimulus support, and the response is usually the solution of an example problem with no prompts from either rules or examples
- $\overline{eg}$ A false or nonexample of the rule.

Evans *at al.*, (1962) describes several different frame types which are made up of these components. The following instructional strategy or sequence of ruleg frame is recommended under this system:

- Begin with a ru + eg + $\widetilde{eg}$ frame which presents a verbal statement of the rule, a complete example of the rule, and a partial example which requires a response from the student.
- Gradually withdraw stimulus support with the use of such frame types as ru + $\widetilde{eg}$, eg + $\widetilde{eg}$, and eg + $\widetilde{ru}$.
- The instructional sequence should terminate when the student can deal effectively with $\widetilde{\widetilde{eg}}$ frames and $\widetilde{\widetilde{ru}}$ frames.

- When two or more rules are being presented, $\widetilde{ru}_1 + \widetilde{ru}_2$ and $\widetilde{eg}_1 + \widetilde{eg}_2$ frames should be used to help the student discriminate between the two rules.

It is further suggested that, to insure adequate generalization, the examples corresponding to a given rule should be as diverse as possible, with the first example being the simplest possible nontrivial example.

Task Variables. There are many task variables which affect the efficiency and effectiveness of an instructional strategy or sequence for teaching rule-learning or problem-solving. Those variables considered to be of major importance are described below.

- *Availability of Verbal Statements of the Rule*. Both Gagne (1970) and Evans *et al*., (1962) recommend that the student be presented verbal statements of the rule at the beginning of the instructional sequence. The presentation of the rule at the beginning reduces the risk of having the student induce an incorrect rule. The verbal statement also serves as a cue to the learning of the new rule. A study by P. F. Merrill (1970) revealed that the presentation of verbal statements of the rules reduce the number of examples and the amount of time required to learn rules,. The presentation also increases performance on a transfer test.
- *Number of Examples*. The specification of the number of examples to be used is dependent upon the difficulty of the rule, the abilities of each individual airman, and the amount of generalization required. It is anticipated that this task variable will be one of the major individualization parameters. The optimal number of examples required in a given sequence can only be estimated prior to the first administration of the program.
- *Type of Examples*. The examples used with each rule should vary in difficulty, and be as diverse as possible from one another. These variables have been shown to be of considerable importance in research with concept-learning (Tennyson, Woolley, & M. D. Merrill, 1972), but little empirical research has been done with rule-learning. M. D. Merrill and Tennyson (1971) also have found that the availability of negative or false examples is an important variable in concept learning. The importance of negative instances in the learning of rules has not been established at the point.
- *Amount of Practice*. This variable is concerned with the number of times a student should be required to apply a given rule. It is anticipated that this variable is related to individual differences, the complexity of the rule, and the uniqueness of various cases of the rule.
- *Memorization of the Verbal Rule*. Gagne (1970) emphasizes that memorization of the verbal statement should not be considered as rule-learning. However, it is possible that the ability to state the rule verbally would allow the student to be able to talk about the rule on a later occasion and may serve as a valuable cue and/or memory aid for subsequent application of the rule.
- *Prompting*. Some students have difficulty realizing the relationship between a verbal statement of a rule and its application in an example or problem situation. M. D. Merrill and Tennyson (1972) found that the presentation of written prompts which point out the relationship between concept instances and the corresponding definition of the concept facilitate subsequent classification behavior. Although this variable has not been studied in rule-learning situations, it is anticipated that the availability of prompts will be an important variable in rule-learning.
- *Amount and Placement of Review*. The results of two experimental studies conducted by Gay (1971) showed that one review is more effective than no review, regardless of the temporal position in the retention of mathematical rules. However, optimal retention over a 3-week interval is obtained with two reviews, one early and one delayed. .
- *Student Characteristics*. P. F. Merrill (1970) investigated the interaction of cognitive ability with the availability of rules in learning an imaginary science by computer-assisted instruction. He found significant ability by treatment interactions using test item response latency as criterion and individual reasoning tests as co-variables. Reasoning had a high negative relationship to test item response latencies for *Ss* in an example-only group, but this

relationship was significantly smaller for *Ss* who received verbal statements of the rules in addition to examples. Therefore, Merrill concluded that the presentation of rules effected a reduction in the requirement for reasoning ability. Dunham and Bunderson (1969) investigated the effect of decision-rule instruction upon the relationship of cognitive abilities to performance in concept problems. The results indicated that different abilities were important in the two conditions. Associative memory and induction were important in the no-rule instruction condition, while general reasoning and induction were important in the decision-rule instruction condition.

Gagne (1970) argues that one of the main individual characteristics affecting rule-learning is the individual's ability to perform the prerequisite intellectual skills which are subordinate to the new rule in question. Therefore, an efficient instructional strategy must be able to adapt in such a way as to provide instruction for students who do not know the component concepts of a rule or are not able to apply rules which may be subordinate to the new rule to be learned.

Gay (1969) investigated the effectiveness of using a preinstruction retention index to predict the number of examples each student should receive in learning mathematical rules. The retention index was based on an empirical determination of the optimal number of examples each individual needed in order to maximize his retention of preinstructional rules. After determination of the retention index, all subjects were randomly assigned to one of three treatments – (1) the subjects in the variable example group were presented mathematical rules in which the number of examples presented for each rule was based on the subject's optimal number of examples on the preinstruction task, (2) each subject in the choice group was allowed to determine the number of examples he would receive for each rule, and (3) the subjects in the fixed group were given exactly three examples per rule. The results revealed a significant sex-by-treatment interaction. Females in the variable example group performed significantly better on both immediate and delayed retention measures than females in either the choice of fixed group. However, males in the choice group performed better on both retention measures than males in the other two groups.

Recent research into the teaching–learning process has focused on the learner as an active analyzer and synthesizer. DiVesta and his associates at Penn State (1970,1971) in formulating an "Evolving Theory of Instruction," have stated that: "No matter what message is presented or what teaching method is used, instruction provides only potentially effective stimuli for the student. If the message is to become effective, the learner must be motivated to attend, and he must have a cognitive structure requisite for appropriately analyzing the message." (DiVesta, 1971, pg. 1)

The learner, therefore, brings to the learning process styles and strategies which enable him to learn. Studies (DiVesta, 1970) investigating two states of the theory which relate to learner style (analysis of the instructional messages and synthesis of the learning outcome) have provided the following information about learner strategies:

- Evidence was presented that the learner's preference for visual or auditory modality determines which features of the instructional message actually are recorded in the learner's sensory register.
- Motivations exist to seek out particular parts of a message for further attention.
- The motivational effects of stimulus characteristics vary in a predictable manner contingent upon the learner's immediate prior experiences.
- Provided the learner is motivated and the instructional message registers, then particular instructional methods seem to facilitate the learner's analysis activities. Instances of facilitative instructional methods include:
  - Providing adequate contextual cues within the message
  - Instructing common elements of the message together.
- Authoritative guidance has differential effects on analysis in problem-solving situations, contingent on the dogmatism of the learner.

Several additional studies are in progress dealing with the second, or synthesis, stage. These relate to the effects of different testing procedures on the learner's interpretation of the desired instructional outcome; differential effects of anxiety and tasks demands on desired outcome of creative responses; transformational processes; and instrumental activities (*e.g.*, note-taking behaviors, recitation exercises).

Description of the Adaptive Model for Rule-Learning

The adaptive instructional model for rule-learning proposed in this section utilizes linear regression models and heuristic decision rules in an iterative cybernetic process to select and sequence instructional components in instructional strategies which are idiosyncratic to individual students. The instructional components will be selected from interrelated and cross-referenced component pools. The components to be utilized in this model are an adaptation and extension of the Ruleg system. (Evans *et al.*, 1962):

ob–Display of a verbal statement of the behavioral objective related to the rule

ru–Display of a verbal statement of the rule

$\widetilde{ru}$–An incomplete or partial statement of the rule which requires the student to respond by completing the rule

$\widetilde{\widetilde{ru}}$–A terminal situation which requires the student to state the rule with minimum stimulus support

eg–An example of the rule

$\widetilde{eg}$–An incomplete example or problem which requires the student to respond by completing the example or solving the problem

$\widetilde{\widetilde{eg}}$–A terminal situation in which the student is required to solve example problems with minimal stimulus support

$\overline{eg}$–A false or negative example of the rule

pr–Prompt, a verbal description of how the example relates to the rule

fb–Display of feedback concerning the correctness of a student's response to a problem or partial example

n(eg)–A series of n examples of the same rule

n(eg + pr)–A series of n examples with a corresponding prompt for each example

ru1–A verbal statement of Rule 1 as contrasted with Rule 2, etc.

eg2–An example of Rule 2 as contrasted with an example of Rule 1 or Rule 3

n(eg + fb + pr)–A series of n example problems with corrective feedback for each problem and prompting for those problems answered incorrectly.

According to the proposed model, these instructional components would be selected from component pools and integrated into a sequence of instructional frames. A sequence of such frames for teaching a given rule may be thought of as an instructional strategy for that rule. It is obvious that the instructional components could be combined in an extremely large number of different frames which could, in turn, be sequenced in many different orders. However, on the basis of the theoretical and empirical studies reviewed in this section, an instructional sequence for rule-learning is proposed in Figure 8. Each line in the figure represents a frame composed of instructional components described previously. The instructional sequence consists of the successive display of frames beginning at the top and proceeeding to the bottom of the figure. This strategy presents an objective, rule, example, example problems, corresponding feedback, and prompts. The supporting stimuli such as objectives, rules, examples, and prompts are faded gradually until the student is able to solve problems and state the rule with minimal support. The model assumes that only very low-ability students would need to proceed through every frame in this exhaustive instructional sequence. Most students would be able to skip some of the fading frames, while very high-ability students might be able to skip the highly prompted frames and some of the fading frames. The instructional sequence or strategy for a given student will be determined through the use of linear regression models and heuristic decision rules.

A proposed review and integrative sequence or strategy is presented in Figure 9. This sequence would be presented after several rules have been learned. Again, the extent and frequency of this review strategy would be determined on an idiosyncratic basis by the adaptive model.

Figure 10 is a flow diagram of the overall adaptive instructional model for rule-learning. When a student enters the rule-learning model, it is necessary to determine if he possesses the intellectual skills

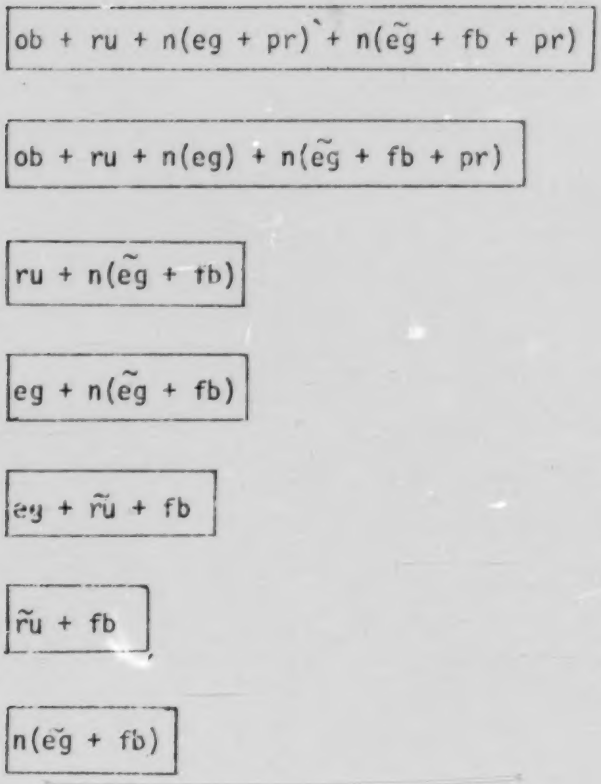


Fig. 8. Sample Instructional Strategy for Rule-Learning.

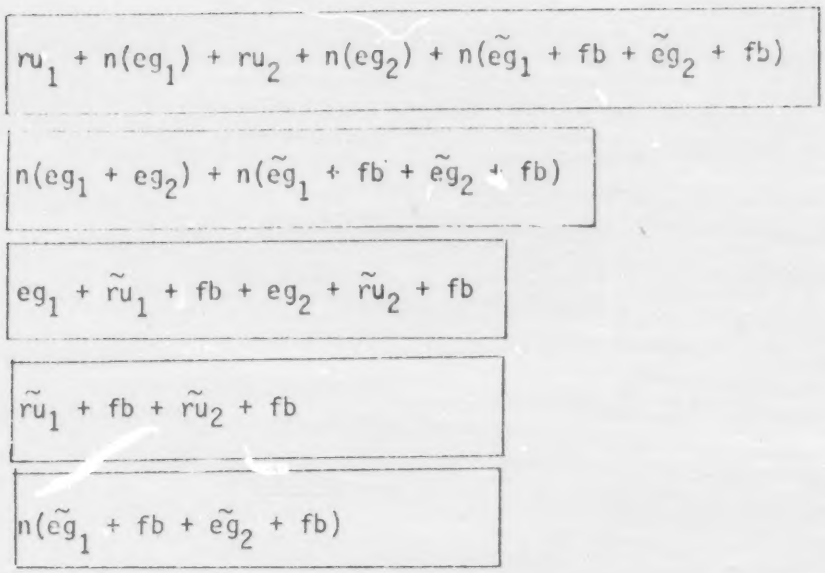

$ru_1 + n(eg_1) + ru_2 + n(eg_2) + n(\tilde{eg}_1 + fb + \tilde{eg}_2 + fb)$
$n(eg_1 + eg_2) + n(\tilde{eg}_1 + fb + \tilde{eg}_2 + fb)$
$eg_1 + \tilde{ru}_1 + fb + eg_2 + \tilde{ru}_2 + fb$
$\tilde{ru}_1 + fb + \tilde{ru}_2 + fb$
$n(\tilde{eg}_1 + fb + \tilde{eg}_2 + fb)$

Fig. 9. Sample Instruction Strategy for Review and Integration.

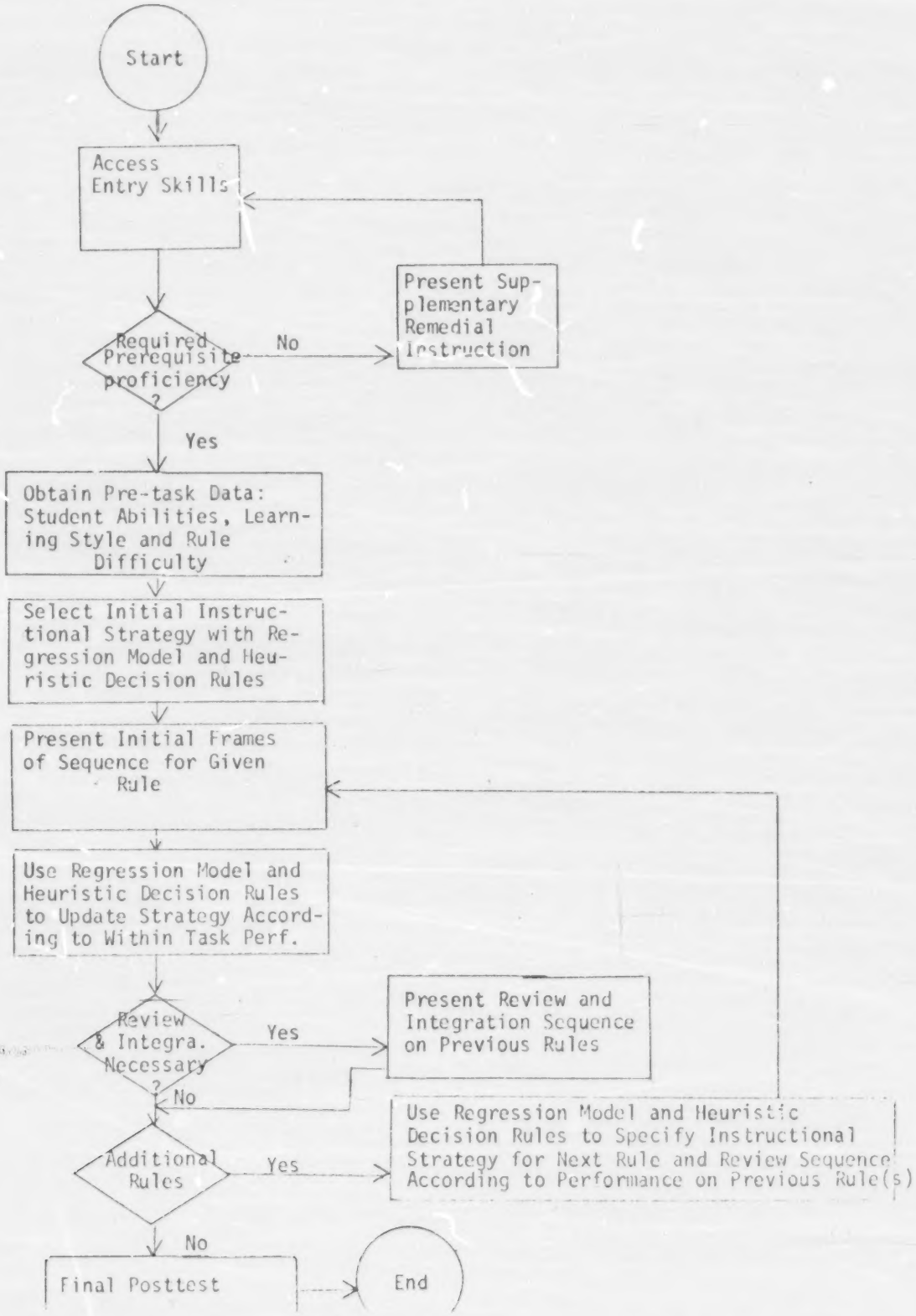

Start
Access Entry Skills
Present Supplementary Remedial Instruction
Required Prerequisite proficiency ?
No
Yes
Obtain Pre-task Data: Student Abilities, Learning Style and Rule Difficulty
Select Initial Instructional Strategy with Regression Model and Heuristic Decision Rules
Present Initial Frames of Sequence for Given Rule
Use Regression Model and Heuristic Decision Rules to Update Strategy According to Within Task Perf.
Review & Integra. Necessary ?
Yes
Present Review and Integration Sequence on Previous Rules
No
Additional Rules
Yes
Use Regression Model and Heuristic Decision Rules to Specify Instructional Strategy for Next Rule and Review Sequence According to Performance on Previous Rule(s)
No
Final Posttest
End

Fig. 10. Flowchart of Adaptive Instructional Model of Rule-Learning.

which are prerequisite to learning the new rules. If the student is unable to apply prerequisite rules or classify instances of component concepts which make up the new rules, then he should receive supplementary remedial instruction. It is also necessary to obtain data concerning personological variables such as cognitive abilities and learning style which may be useful in predicting an appropriate initial instructional strategy for each student. These data, along with data concerning task characteristics such as the difficulty level of a given rule and corresponding examples, will be utilized by the linear regression models and decision rules to select instructional components to make up an initial instructional strategy for a given student. The generated instructional strategy is then presented to the student. Within-task performance data, such as display latency, number of items correct, and test item response latency, will be collected as the student proceeds through the generated instructional strategy. These data are then utilized by linear regression models and decision rules to modify or update the instructional strategy as necessary. For example, if a student is performing poorly under the instructional strategy, it will be necessary to present additional frames with a high level of prompting and a greater number of examples with a slow removal of stimulus support. On the other hand, if a student proceeds very rapidly through the displays and solves all problems correctly, it may be possible to remove stimulus support more rapidly and to present fewer examples and/or prompts. The student's performance on the terminal items for a given rule will then be utilized to specify the instructional strategy for subsequent rules. The student's performance on previous rules is also utilized to specify the frequency and type of review and integration strategy which will be utilized for a given student (Figure 9). This iterative and cybernetic procedure is followed until all rules for a given series are learned.

The following have been identified as possible input variables to the model:

- Difficulty level of a given rule
- Difficulty level of examples
- Number of rules in a series
- Entering cognitive abilities such as general and inductive reasonings
- Preinstruction retention index
- Learning style, such as dogmatism and modality preference
- Within-task performance measures such as display latency, number of items correct, and test item response latency
- Within-task state variables such as state anxiety and subjective confidence.

The adaptive instructional model for rule-learning will manipulate the following instructional variables as output:

- Number of examples
- Type of practice problems
- Number of practice problems
- Level of prompting
- Rate of stimulus support fading
- Amount and placement of review and integrative materials.

The adaptive instructional model for rule-learning presented in this section is based on the theoretical and research literature available at this time. However, the model contains many innovative features which have yet to be implemented and validated. Considerable research will need to be done in order to refine the model. However, it is felt that the model presented in this section is a rational starting point and will provide the framework in which to make future refinements and to investigate those variables which are crucial in the instruction of rules. A simulation of this model would require further delineation of the linear regression models and heuristic decision rules required to predict and specify appropriate instructional strategies. The input variables and instructional decisions listed previously may be expanded or revised based on the properties and constraints of the heuristic decision rules to be developed. Further basic

research into the role and effects of number of examples, prompts, type of examples, amount and placement of review, and rule frame structure and sequence will facilitate the generation of appropriate regression models and decision rules.

Description Models for Problem–Solving

The current state-of-the-art only allows a very tentative statement of an optimal instructional strategy for teaching problem-solving behavior. According to Gagne (1970) the following conditions are required for problem-solving. The student must be able to recall the previously learned rules which are relevant to the problem solution. In the learning situation, he suggests that verbal instructions should be used to help the learner recall relevant rules in close time succession. He further suggests that verbal instruction should be used to guide or channel the thinking of the learner in certain directions. This guidance should always come short of describing the solution itself. However, as a minimum, it should include a description of the goal and the general form of th solution in order to limit the range of hypotheses.

Although Gagne states that repetition does not appear to be an important condition for problem-solving, since wh. ' is learned is highly resistant to forgetting, it seems apparent that the educational process should ... le increased opportunities for students to be involved in problem-solving situations. By increasing stu... ' exposures to a wide variety of problem-solving situations, their skill in solving unique problems will be .ncreased.

Gagne (1966) also suggests that several individual differences may be related to problem-solving behavior. Applied to the AIS setting, these individual differences could be stated as follows:

- The number and variety of rules relevant to problem solution that a student may call upon
- The student's ability to recall relevant rules
- Differences in a student's concept distinctiveness
- Ability to generate hypotheses
- Ability to match specific instances to a general class in order to verify solutions.

Perhaps the most fully developed model that could be applied to the teaching of rules and problem-soiving is Task Teach (Rigney, 1969), a computer time-sharing system used to assist the learning of a variety of tasks. including operating equipment and troubleshooting problems in the equipment. A definite distinction is made between two different types of serial action tasks. The first type include prescriptively guided tasks which can be completely specified before they are performed. Included in this type is the operation of specific test equipment. In contrast, a problem-solving or troubleshooting type of task would have choice points and decisions required for completion. Both linear tasks and intricately branching tasks (where the next subtask is contingent upon the outcomes of previous subtasks) may be handled in the Task Teach Program.

The main adaptive feature of the Task Teach Program is the high degree of learner control. The learner is allowed to operate in any of four different modes which provide varying levels of support and guidance. Mode 1 provides maximum guidance, Mode 2 provides moderate guidance, Mode 3 is a self-test, while Mode 4 is a final examination of the student's performance. In addition, several commands are built into the program which allows the student to have extensive control over the sequence and amount of support he receives. The "map" command gives the student a diagram of the task structure which identifies the action goal hierarchy he must accomplish. For problem-solving or troubleshooting tasks, a decision tree may be represented. Under "monitor" support, the Task Teach Program automatically monitors student errors and gives the student appropriate feedback. The "progress" command gives the student a list of remaining possible malfunctions or all goals accomplished up to that point. The "explanation" command gives the student reasons why certain tasks should be performed within certain subgoals. The "next" command lists the next actions which should be performed or reviews how to perform them. The "history" command gives a response-by-response record of everything the student has done to that point. The "restart" command allows the student to start over or switch to a new task, while the "quit" command allows him to sign off the system. Within each of these commands the amount of prescription versus interactive material varies.

The present student interface is a teletype terminal with a student-operated carousel slide projector. However, plans for interfacing the slide projector with the terminal, of using CRT devices, and also for interfacting the actual test equipment or simulated training aids with the computer are being considered.

The Task Teach Program has general applications and could be used with any serial-type task. Efforts have been made to simplify the use and entering of the parameter data by the instructional designer without having to learn a CAI language. While all that is required is the input of lists representing the structure of the task, a sophisticated task analysis of the task must be conducted by the instructional designer prior to entering the lists. A knowledge of the list format is also required. It is not necessary, however, for the author to program all possible task lists since the student control commands are used to call up separate subroutines.

This approach has very definite application for Air Force courses, particularly PME which entails considerable equipment operation and troubleshooting activity. Such a program would provide considerable opportunity for the student to practice operation or troubleshooting skills with only necessary assistance and feedback.

Simulated problem-solving experiences can provide students with the opportunity to learn complex concepts as well as skills through participating in lifelike experiences without the high cost and risk involved in the actual task. In a computer-based instructional simulation, programming techniques are incorporated to monitor and analyze the student's work in the performance of assigned training tasks automatically. These techniques provide information for diagnosis of learning difficulties and lead to the development and testing of hypotheses related to overcoming the problems.

Feurzeig and Lukas (1971) describe two computer-based simulations for complex operational tasks which incorporate this feature. The first task implemented and tested involved perceptual and motor skills to maintain an aircraft in a holding pattern solely from information provided by instrument indicators. A monitor system for this task was implemented and used with both new and experienced pilots. The general approach was to design a highly task-specific system of programs, called an instructional monitor, for following a student's work and diagnosing his difficulties along the way. Such a monitor requires detailed information on the various kinds of errors possible, Procedures for diagnosing specific errors in terms of observable effects, and associated information about possible reasons for errors in faulty procedures or conceptualization. This information provides the basis for instructional decisions. In the simulation, the trainee was given the task of flying a vehicle over a prescribed course on the basis of instrument information. The vehicle is represented as a moving point on a scope which also displays the appropriate changing instrument information: altimeter, automatic direction finder, magnetic compass, and rate of return indicator. The location of the vehicle, the ground track for the course, the instrument indicators, and the trainee's actual flight path can all be displayed. The trainee controls the vehicle through the use of a joy stick linked to the computer. The problem may be complicated by the introduction of winds, drift of the controls, and variations in altitude. As a student proceeds in his flight, the state of the forced dials and the position of the plane at each clock interrupt are stored in the computer. When he has completed the task, the trainee may review his flight in its entirety by calling on the replay monitor. This program plays back the flight displaying both the instruments and the holding pattern along with ground track. The replay monitor also attempts to detect the trainee's local errors and to make appropriate comments. The monitoring and simulation system was tested and evaluated in an instructional experiment. The subjects had flying experience spanning over a wide range of hours before the experiment began. The monitor systems was used to train trainees to fly holding patterns at the computer with some degree of accuracy. An actual flight testing of the trainees was then carried out to see if this skill carried over to the real task. The trainees showed considerable success in transferring from the computer-training situation to the actual flight situation. They demonstrated facility with the use of the quipment and good comprehension of the principles involved in performing the holding task under moderate wind conditions. The authors suggested that appropriate instructional programs of the same kind can also be designed for use with many other complex perceptual motor tasks.

A second task area reported involved the acquisition of perceptual skills essential to ship maneuvering and collision avoidance. This task area involved a graduated sequence of course-estimation problems presented on a simulated PPI screen and permitted both the gradual acquisition of skills and isolation of conspicuous learning difficulties. Related studies provided a framework for detecting deeper underlying difficulties which show up in more complex realistic situations. While these studies used a very small sample

complex tasks involving mechanical and perceptual, as well as intellectual, components. This kind of extension is particularly important in making many areas of technical training both feasible and more cost-effective. There is great potential in courses such as Weapons Mechanic for simulation of troubleshooting problems; problems both greater in number and with more dangerous consequences than could ordinarily be presented to trainees.

Computer simulations have also been used to provide the student with lifelike whole job experiences. Direct Support Unit Simulation Exercise (Powe, 1969) is one such example. In a dynamic representation of under-fire conditions, the student is required to perform tasks as supervisor of a Direct Support Unit responsbile for missile system repair. Decisions are required based on given situations involving personnel operations, security, supply, repair of malfunctions, backlog, length of workday, maintenance of organic equipment, liaison, and military unit training. The student has available administrative and technical publications as well as supply and maintenance documents with his goal being to make logical decisions under realistic conditions.

This type of simulation would be especially appropriate in the Inventory Management course where students need experience in seeing the entire scope of their occupation, which has typically not been possible for them in traditional training conditions.

Each of the instructional programs for teaching problem-solving provides opportunity to learn appropriate techniques to approach finding the solution to a problem. It is obvious that application of rules in problem-solving requires knowledge of a variety of rules, the choice of the appropriate rule, and the correct application of the appropriate rule. To develop these skills, varying amounts of practice are required in simulated and in actual situations. It is on the dimension of amount of practice, as well as the dimensions of varying the amount and degree of prompting or guidance during the instructional sequence, that adaptation to individual difference might be made.

Recommendations

The following recommendations are made:

- Although the adaptive model for rule-learning proposed in this section is based on current theoretical and research literature, many features of the model are innovative in nature and will require additional research and validation. It is, therefore, recommended that research be conducted in this area. In addition, the linear regression models and heuristic decision rules utilized by the adaptive model will require further delineation and empirical validation.
- A simulation of the adaptive model will facilitate the specification of initial decision rules and regression algorithms. The input variables and instructional decisions should be expanded or revised according to the constraints and characteristics of the simulated adaptive model. It is recommended that two versions of the model be simulated–a full and a reduced model. The full-version model would require a highly interactive mode of instruction such as CAI. However, a reduced-version model could be utilized in a semi-interactive mode such as CMI. Therefore, it is recommended that both models be simulated. The reduced version would not require an updating of the instructional strategy according to within-task performance data.
- The applicability and extension of the adaptive model for rule-learning into the area of problem-solving should be investigated. However, it is anticipated that instructional models such as Task Teach might prove to be very useful in problem-solving applications in the AIS.
- Provision for research into the role an effects of the number of examples, prompts, types of examples, rule frame structure, and amount and placement of review should be made in the implementation of the adaptive model. This research would provide data for the revision and refinement of the model.

VI. ALGORITHMIC REGRESSION MODELS

Adaptive instructional models have been in use since the first self-instruction program. Learners have characteristically adapted to the learning environment by choosing the form of studying optimized for them on some variables. These adaptations to accepted instructional technique more often than not were based on incomplete information, often false assumptions about the learner, and contingencies not related to optimum learning requirements. Recent research on learner characteristics, instructional variables, and aptitude-treatment-interactions (*e.g.*, Tobias, 1969; Melaragno, 1967; Cronbach & Snow, 1969; Bracht, 1970) has indicated the potential for adapting instructional techniques along many dimensions in order to match unique learner profiles more closely. Whereas only a few years ago, fine-grained, cybernetically controlled adaptations would have been difficult from administrative and operational points of view, the use of high-speed digital computers in the educational world has made the assignment of learner-sensitive instructional techniques and materials increasingly viable.

Characteristics of Algorithmic Regression Models

A number of instructional systems based on response- and learner-sensitive models have been attempted; some of these were dependent on the availability of a computer. Programmed instruction (Skinner, 1961; or Crowder, n.d.) provided learner-response characteristics to learning tasks which utilized printed media. Individualized instructional programs such as Project PLAN and IPI have been available for a number of years. (Flanagan, 1970; Lindvall & Bolvin, 1966). In these programs, students are assigned instructional modules according to a predetermined scheme based upon reaching criterion on previous materials or on pretest scores. The student is required to progress through a modified "track" system in which the opportunity exists to "jump" from one track to another.

Suppes *et al.*, (1963) utilized a computer to present instructional materials and to make branching decisions on the basis of student-response patterns to the materials being presented. Computer-Managed Instruction (CMI) can also provide for the assignment of either new materials as the student reaches criterion, or remedial materials when he doesn't (*e.g.*, Gallagher, 1970; Lawler, 1971). Although the adaptation described so far is responsive to the learner and appears to approximate the behavior of a teacher, the methods provide, at best, for multiple-track systems utilizing essentially similar instructional materials within each task. It is the purpose of the algorithmic regression adaptive model, described in the next paragraph, to provide for a more comprehensive individualized utilization of media, materials, and diverse instructional techniques.

The adaptive instructional model under consideration in this section utilizes multiple-regression analysis to provide a prediction of the media, content, and instructional method necessary to optimize learning. Of the adaptive models described here, regression modeling is unique in that it utilizes a number of learner characteristics to assign an optimal instructional experience to achieve quantifiable criterion goals. Thus, to the extent that the variables input to the prescription output variables, this model can be expected to predict successfully the media, content, and instructional method best suited to the characteristics of a particular student.

Markov models which have been suggested by Atkinson (1967) were considered to be inapplicable to technical training adaptation problems. The models typically require that the test items or responses which are given in order to make state-changing (branching) decisions be highly and independently homogeneous. This state of affairs is typically not the case as behaviors tend to be heterogeneous and highly related. Furthermore, the transitions which characterize Markov models are of a minute nature which could only transfer to the minute-by-minute course of instruction. Thus, this framework is clearly too detailed and complex as an intertreatment decision process.

The selection of a regression approach for this model is prompted by the quantifiable nature of the prediction algorithm. For the sample of students on whom the prediction model is developed, the error of prediction (represented by the "distance" between the student's actual score and the score predicted, *post hoc*, for him by the model) is at its minimum due to the nature of regression analysis. Regression is typically utilized to investigate the interrelationships between predictor variables such as age, ability scores, or SES, and criterion variables such as success in college or course grades. In the present case, predictor variables such as ability, aptitude, personological variables, and treatment characteristics are used to predict criterion score on a multitude of course performance levels in order to *specify* the optimal instructional treatment.

The regression model being considered will use two classes of variables to select the optimal instructional alternatives. These input variables may be classified as either *trait* or *state* in nature. Trait variables may be characterized as static, long-lasting, and descriptive of the individual's behavior over longtime periods, *i.e.* as indices of expected *general* behavior. *State* variables, in contrast, may be characterized as dynamic, short-term, and descriptive of the individual's behavioral nature within *specific* situations, at particular times, and over shorter time periods.

The trait, historical, or a priori variables which may provide input to the regression models include both background indices such as age, SES, and prior knowledge of similar material, as well as more traditional measures such as IQ, trait anxiety, curiosity, and motivation, personality measures, aptitude indices, and achievement test scores. These trait variables may be considered "historical" since they are available prior to instruction and are not likely to be updated during the weeks or months of ongoing instruction.

The input of state variables to the models include primarily responses and latencies on criterion-referenced test items and traditional achievement test scores, which may be required to assess the student's current learning/aptitude state. Additionally, measures such as state anxiety, curiosity, and motivation may be used to "correct" for current changes from the learner's trait levels.

An additional characteristic of regression models is that multivariate techniques are applicable. These techniques permit the *joint* analysis of the relationships between the vector of input and the vector of output (prescriptive) variables as well as allowing for the prediction of the prescriptive variables under statistical assumptions less stringent than with univariate techniques, making the techniques generally applicable to data in the AIS setting.

Issues to be considered in the use of regression models for adaptive instruction include (1) the determination of the statistical properties of the variables, (2) the selection of the instructional components to be predicted by the regression equation, and (3) methodological requirements for establishing sufficient (Simon, 1969) criterion levels where required.

The determination of the statistical properties of the variables is an important consideration in that the distributions of scores can have a marked effect on the accuracy of the prediction. Markedly skewed score distributions, particularly when accompanied by small variances, lead to a smaller correlation between the linear combination of scores and the criterion to produce lessened effectiveness of the model. The range of scores can have a similar effect on the predictive accuracy of the regression (or algorithmic) model.

The instructional parameters or components to be predicted by the regression equations are selected on the basis of three criteria. The first criterion is the availability of research evidence to support the relationships between the available trait and state indices and the prescriptive variables. Given the current state-of-the-art, if one or more research studies judged to be reliable exists, this criterion will be assumed met. The second criterion relates to the usefulness of the criterion classification to instruction, *e.g.*, media choice is useful, but typeface choice is not. A third criterion relates to the inclusion based on iterative empirical validation. The variables which are being considered are listed in the model structure subsection of this section.

Prior to predicting the optimal level of an instructional prescription factor, it is necessary to establish acceptable criterion levels for each instructional factor to reflect an efficient placement of students. The methodology for determining the criterion levels will be selected during the simulation phase of the project.

Applications in the Advanced Instructional System (AIS)

The primary goal of AIS is to provide a prototype, state-of-the-art, individualized, multimedia, computer-based instructional system which demonstrates cost-effective training procedures. The characteristic of multiple regression analysis for predicting optimal instructional parameters which most clearly relate to the cost-effectiveness constraint is the "least-squared error" solution. This solution of the regression equation provides for minimal differences between the actual scores on criterion measures and predictions of the scores. On the same criterion measures, the empirically derived regression equations provide for the closest match of predicted and actual scores and can be expected to prescribe the most efficient instructional treatment for the operational group of students.

The solution of the regression equation will be determined through an iterative procedure in which initial groups of students are randomly assigned to instructional treatments on a stratified basis. The characteristics of these students and the treatment given will then be analyzed and related to the performance levels obtained. Succeeding groups will then be assigned to instructional treatments leading to the best predicted score by means of the regression equations developed. Periodical updatings and revisions of the model will result in refinement of the roles of various predictors (*e.g.*, elimination, addition, or change of contribution of individual indices) and a maintenance of the model's efficiency.

Role in AIS

The role of algorithmic regression models within AIS is to generate the adaptive instructional prescriptions. Whereas other models described in this report may be characterized as operating at an intratask level, the regression models operate at an *intertask* level. As such, the model is the mechanism for predicting (and thereby selecting) the optimal media, difficulty, and/or instructional method for each learner. It is expected that the *complete* range of predictive choices will rarely be available, but that an array of instructional alternatives will be available at each choice point. Upon the choice of a nonoperable prescription, the closest avalable option would be selected and offered to the student.

This framework for computer-based prescription may be placed midway on a scale with end points characterized as "response sensitive" and "response insensitive." A response-sensitive paradigm would provide for prescription of detailed "frames" of instruction following each student's response, whereas a response-insensitive paradigm would provide for, at best,a track system in which only gross adaptation would occur. The envisioned CMI framework is response sensitive; however, the prescriptive mechanism does not operate following each individual response, but only following a completed lesson. This means that (1) the lesson materials themselves do not need to be presented on-line, (2) the student has more opportunity to use media devices other than a computer terminal, and (3) testing may occur off-line with form-reader computer input following testing.

A secondary role of the algorithmic model lies in the prescription of counseling experiences. Three major contingencies can arise which may trigger this counseling role: (1) resource exhaustion, (2) time-fatigue factors, and (3) situational performance factors. Certain kinds of counseling experiences are necessary as an integral part of optimal course flow. These experiences include counseling related to career goals and requirements, course incentive descriptions, and academic difficulties caused by personal problems. These counseling experiences can be assigned to fill a gap when the resources needed to continue instruction are unavailable to the student. At certain times, such as after a number of hours on-task when a break is needed, some counseling may be assigned as a means of altering a task briefly. Whenever performance falls due to situational factors peculiar to the student, counseling may be assigned. The experiences suggested may involve either an instructor, a professional counselor, or, in cases such as career counseling, a technological approach such as a slide-tape presentation, or a CAI-counseling task may be assigned.

Payoffs for AIS

A number of potential payoffs accrue to the use of a regression model within AIS. First, the operation of the model can be made transparent to the learner. The interface between the student and the prescription of instructional materials begins with a test on previously learned materials and ends with the prescription of new materials. The student need be aware of only these two components. Between them, the adaptive models (regression among them) operate without further input or interaction with either the student or instructor. In the rare case where specialized additional input is required, this is assigned or asked for, but the model's *operation* remains transparent.

A second potential payoff of regression models used in the prescription of learning experiences is the characteristic that assures near-optimal selection of available instructional software media and specialized carrels given proper predictive input. This characteristic can be validated *within the system* to provide a check on the usefulness of the model.

The regression model will operate in real-time, providing near instant response to input so that when a student completes a diagnostic or criterion test, the prescription for the next activity is available as soon as the results are fed into the computer (either through the facilities of a computer-based test or through optical mark reader input.) This will usually happen within a matter of minutes following completion of the test.

Finally, the model may be updated in a cybernetic fashion in order to reflect changes in the relative predictive value of individual predictors as a function of emerging changes in the characteristics of students, the relative quality of instructional materials, or other factors.

Review of the Literature

The literature bearing on regression models falls into two general categories, (1) applications of regression models to adaptive instruction, and (2) studies dealing with the selection of predictor variables for the regression equations.

Applications. Three applications of regression models are described. Two related applications at Florida State University were described by Dick, Rivers, King, and Hansen (1970) and by Rivers (1972). Dick *et al*., (1970) investigated developmental procedures for producing a regression model to make decisions for ongoing instruction in a computer-assisted instructional task in Boolean algebra. Preview frame, criterion, acquisition, quiz performance, latency, and subjective confidence measures were investigated in order to determine the measures which would contribute most to a predictive and useful adaptive decision model. The prediction of quiz score utilized performance, latency, and confidence measures on the criterion questions. Prediction of final examination score used performance, latency, and confidence measures on the quiz questions. Prior to the time the student completed either the quiz or the final examination, a prediction was made of his test performance. Remedial instruction was provided whenever the predicted test score fell below the mean established by a prior group of students. The results of this investigation were equivocal. In one unit, the adaptive model identified students who needed remedial instruction. Even though the students started instruction with scores below those of students in a reference group, scores on the final examination were comparable. A second unit did not produce usable results due to a mismatch between the diagnostic questions and the difficult training materials.

Rivers (1972) investigated the relationship between within-course variables and achievement in the course. Correlational and regression analyses were used to identify the relevant predictor variables and remediation points. During the first phase of the two-phase study, 33 female subjects were administered trait and state-anxiety inventories (STAI, Spielberger, 1969) and then proceed through a program in health education describing the incidence and risk of contracting heart disease and the diagnosis of myocardial infarction. During learning, percent correct answers and response latencies were obtained for each student, and regression equations were computed from these data.

During the second phase, cumulative performance and latency, as well as the most recent performance and latency, were used as predictors of the posttest score for each of the nine concepts involved in the program. Whenever the predicted score indicated performance would fall below the acceptable level of 80 percent, instruction was prescribed. A total of 80 female students were used to validate the regression models. The results indicated that use of the regression model led to improved performance on the posttest. A control group which received remediation on all concept also improved, but the group took more time and did not score as high on the criterion test as the regression model group. It is clear from this research that the regression model provided a means for assuring that students who required remedial instruction were given it. The time savings shown, although small compared to the all-remediation group, would amount to a large savings over the duration of a course. It may be noted that the regression model group did *not* take significantly more time than either a "student choice" or a "no remediation" group taking the same instruction.

Input variables. The input variables may be considered along the framework proposed by Cronbach (1967). Adaptation to individual differences may be characterized by the natures of the educational goals, the instruction provided to the student, and the modifications to the treatment in order to meet the students' needs. Table 2 briefly describes the framework which Cronbach proposed. The regression approach which FSU is pursuing is an elaboration of the framework for goals fixed within a course with

TABLE 2.

PATTERNS OF EDUCATIONAL ADAPTATION TO INDIVIDUAL DIFFERENCES

Educational goals	Instructional treatment	Possible modifications to meet individual needs
Fixed	Fixed	1a. Alter duration of schooling by sequential selection. 1b. Train to criterion on any skill or topic, hence alter duration of instruction.
Options	Fixed within an option	2a. Determine for each student his prospective adult role and provide a curriculum preparing for that role.
Fixed within a course or program	Alternatives provided	3a. Provide remedial adjuncts to fixed "main track" instruction. 3b. Teach different pupils by different methods.

(From Cronbach (1967)).

alternative instructional treatments. Cronbach gives two dimensions of modifications The first dimension, and that along which Dick *et al.*, (1970) and Rivers (1972) have operated, provides for remedial alternatives to an otherwise fixed instructional program. Cronbach devotes considerable attention to the description of the adaptation of instruction to individual differences by altering the instructional method utilized (3b. in Table 1). The investigation of aptitude X treatment interactions (ATI) is directly related to this application. Where ATI's are shown, differential instructional treatments may be administered to students who differ in the related ability, aptitude, achievement, personality, and affective characteristics.

Aptitude X treatment interactions have been discussed by Bracht (1970) who analyzed 90 studies, only 5 were shown to produce significant *disordinal* interactions. Bracht defines a disordinal interaction as one in which the treatment differences at two or more levels of the independent variable are both significantly nonzero and different in algebraic sign. In other words, the lines on the graph of the means must cross, indicating that learning treatments are differentially effective at different points of the individual difference continuum. The four research studies which resulted in significant disordinal interactions and which are related to the present report may be summarized as follows:

(1) Atkinson and Reitman (1956), found that students low on affiliation motive performed better with an achievement-orientation treatment and students high on affiliation motive performed better with a multi-incentive treatment.

(2) In an experiment by Marshall (1969) students from poor educational environments performed better on a high-interest task whereas students from good educational environments performed better on the low-interest task

(3) Thompson and Hunnicut (1944) reported that introverts obtained higher cancellation scores when they received praise, while extroverts obtained higher cancellation scores when they received blame.

(4) Van De Riet (1964) found that underachievers performed better when they received criticism and normal achievers performed better when they either received praise or were asked unrelated questions.

The variables indicated above would appear to be fruitful input for an instructional model within the present context. To summarize, they are (a) affiliation motive , (b) prior educational environment, (c) introversion-extroversion, and (d) prior achievement versus potential levels.

Additional research by Snow, Tiffin, and Seibert (1965), O'Neil (1970), and Tobias (1969) suggest that other variables such as anxiety level, attitude, and creativity might relate to instructional methods. Less stringent constraints on the selection process would allow ordinal interactions to be utilized. Some of these relations will be described briefly in the following paragraphs.

Snow, Tiffin, and Seibert (1965) investigated the effects of differential learner characteristics and prior knowledge on immediate and delayed recall performance from both filmed and live physic lecture demonstrations. In an analysis of immediate recall, 225 "film" students and 212 "live" students were used. Due to factors such as dropouts, a smaller number was used in the analysis of long-term retention. No overall differences in performance levels were found, but a significant difference in the amount learned was shown for the live-presentation group among students holding negative opinions about films. The authors concluded that passive observers lacking self-confidence performed higher, but not significantly so, on films. Those high in numerical aptitude having no previous knowledge performed better in a live mode. A tendency was observed for low-aptitude students with prior knowledge of the subject matter to perform better in the film condition.

The effects o stress on state anxiety and performance were investigated within a computer-assisted instruction task by O'Neil (1970). Stress was induced by caustic feedback concerning performance. Trait anxiety and the number of errors within the task showed no relationship to stress. However, state anxiety levels were shown to be related to the number of errors within the task. Students with high-state-anxiety scores made more errors during the CAI task than students with low state-anxiety scores. However, the difference in number of errors was significant only in the easier portions of the task.

In an investigation within a programmed instructional text, Tobias (1969) found creative students had higher performance scores regardless of whether a constructed response or a reading mode was used, but that achievement was higher on technical material (in contrast to familiar material) for the constructed response group. Large differences were indicated between reading and constructed response conditions for low-creativity students, particularly on technical pictorial subject matter.

Model Structure

A regression approach to adapting instruction will be developed which is, in part, based on the research cited in the preceding paragraphs. A generalized flow diagram is presented in Figure 11. Linear regression techniques with the least-squares criterion will be used to predict optimal uses of instructional resources by individual students. The instructional resources include the following:

- Media options
- Difficulty level
- Redundancy level
- Remediation
- Content and sequence
- Instructional method
- Hands-on/laboratory tasks

The algorithm is the critical element in the construction of the student's learning prescription consisting of the previously listed output variables. As distinct from the adaptive models to be considered which provide for within-task decision structures, the algorithmic regression model under consideration here may be thought of as a *between-task* model, making possible a more complex decision structure.

The algorithmic model will operate in real-time, providing learning prescriptions based on up-to-the-moment assessment of the student's history and current learning progress. For this reason, both trait or entrance variables, as well as state or concurrent variables, will be used in various combinations as independent variables in the prediction equations.

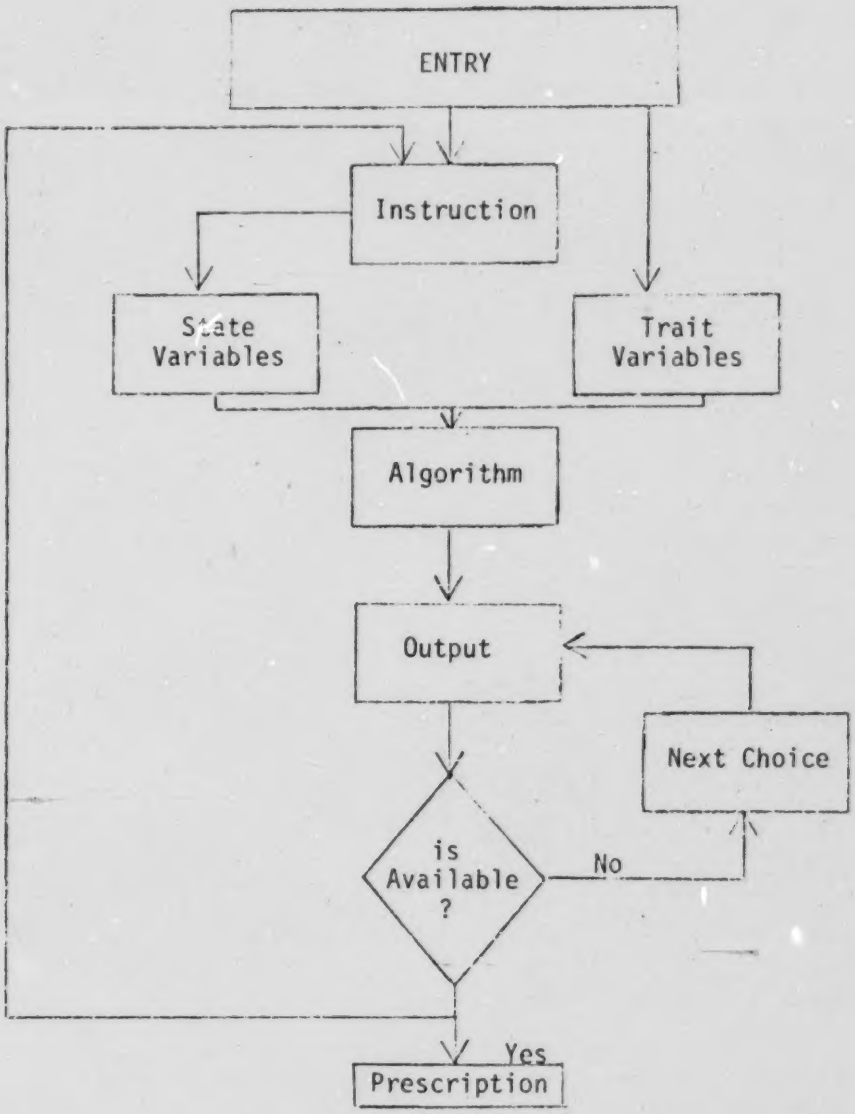


Fig. 11. Generalized Flow Diagram of Adaptive Regression Model Operation.

As a preliminary starting point, the following items have been identified as potential trait variables:

- AQE score
- Mechanical aptitude scores
- Electrical aptitude scores
- Verbal aptitude scores
- Trait anxiety (STAI) scores
- Trait motivation scores
- Trait curiosity (OTIM) scores
- General confidence measures
- Opinions related to school, media, the military, and the career field
- Prior knowledge of course material.

State indices, *i.e.*, those which represent current and changing indices of the student's learning parameters, have been identified as follows:

- Recent performance scores
- Errors on last unit
- Confidence level
- Mean response latency
- State anxiety (STAI) scores
- State curiosity scores
- State motivation scores
- Student's choice of future course flow.

The input variables described will be utilized during a validation phase and the lsit will be amended as indicated by the results of the validation. The literature reviewed in Section IV indicates that these variables are related to learning in such a way as they can predict a learning level, or the variables are readily available (such as AQE) and can reduce the error variance inherent in the prediction equations.

Recommendations

Five recommendations concerning the use of regression equations for adapting instruction emerge from an analysis of the method and its feasibility. These recommendations are as follows:

- Bruner (1966) has made the distinction between descriptive theories of learning and a prescriptive theory of instruction. The regression model approach bridges the gap between description and prescription by utilizing descriptive measures which have been shown to be predictive. A prescriptive model is thus derived from a descriptive one. For this reason, the regression approach is recommended for selecting instructional prescriptions in AIS.
- Second, the regression approach appears to be especially useful in an interlesson context. Rather than changing or modifying the instructional method *within* an instructional session on the basis of responses,a potentially more effective instructional change can be made by directing the student to another set of materials within the lesson or to a remedial or enhanced lesson.
- A third recommendation concerning the use of regression models focuses on the interface between this and other models with the process of allocation of instructional software and hardware. The interface itself has two dimensions. The first dimension relates to selecting resources that match an ideal prescription. A table-look-up procedure of some kind may suffice for this activity. The second dimension deals with the assignment of resources that may or may

not be available due to use by other students or within a repair/replacement cycle. This dynamic allocation procedure must exist in conjunction with, yet in addition to, the present instructional model.

- It can be expected within an operable training system used to capacity that the prescription selected by the regression equation as optimal may be unavailable. A necessary interface to the regression model formulation is a resource allocation model which would provide a list of available resources and estimates of resource use so as to permit optimal resource-spares to be ordered. Thus, not only will more efficient use be made of available resources, but resources can be maintained at an efficient level of supply as well. It is, therefore, recommended that a resource allocation model be developed as a part of AIS.
- As a fifth recommendation, validation of the regression models should be carried out over a sufficient period of time by the AIS contractor in order to provide sufficient data to update the beta weights, if required. The contractor should also devise a procedure for periodic revalidation and restructuring of the models.

VII. DYNAMIC PROGRAMMING

Characteristics of Dynamic Programming Models

Dynamic programming, developed by Bellman (1957) and his colleagues at the Rand Corporation, grew out of a need for optimization in the war effort in the 1940's. Dynamic programming continued in the 1950's in areas of industrial and other institutional problems. Operations research, as this scientific approach to the solution of industrial problems has become known, incorporates the formulation and application of mathematical models of optimization to the solution of instructional problems. Extensive applications of the techniques of dynamic programming have been made in inventory theory, allocation problems, control theory, search theory, and chemical engineering design. Because many of the principles involved in industrial problems also apply in the field of technical training, the techniques of dynamic programming can be utilized in the solution of allocation problems in an adaptive model in the AIS setting, or extended to become the AIS master model by monitoring and controlling other instructional subsystems.

Basically, dynamic programming takes a sequential or multistage decision process containing many interdependent variables and converts it into a series of single-stage problems, each containing only a few variables. Bellman's dynamic programmming principle of optimality states, "an optimal set of decisions has the property that whatever the first decision is, the remaining decision must be optimal with respect to the outcome which results from the first decision" (Bellman, 1957). Since dynamic programming essentially looks at a problem having N decision variables as N subproblems, the development of the high-speed computer has facilitated the high volume of computation that is required for an optimal solution.

Dynamic Programming in the AIS

Dynamic programming is a technique that holds great promise in the area of decision-oriented systems in education. Such techniques allow for realistic modeling of the educational decision-making process. Dynamic programming techniques based on mathematical models are attractive as planning devices because they permit the specification of certain original states of a system, certain desired terminal conditions or targets, and then a search for the levels of system controls which will produce the desired end result within the constraints of cost and time, as predetermined by the overall system in which the instruction takes place.

Since the Air Force technical training is complex system composed of many variables, a modeling process should produce results that are more accurate than mere intuitive or even empirically based heuristic decision processes. In considering the mass of students, the vast requirements of the Air Force technology, and the considerable expense that is necessary to perform the kind of technical training required, it is obvious that a sophisticated mathematical model could produce decisions that would ensure greater efficiency of the training. The allocation of instructional resources, if handled in a dynamic and responsive manner would utilize the available resources maximally and provide feedback data regarding the

necessity of additional resources. If dynamic programming techniques were used simply in the area of allocation of instructional resources, a maximum usage of each resource, with minimizing cost, would result.

Another concern of any technical training institution is that of optimization of time requirements for the student to attain the desired criterion performances. By employing dynamic programming techniques to monitor time requirements of students' progress through any instructional sequence, more effective remedial and branching techniques could be used. Utilizing dynamic programming techniques would ensure that all students would complete the instructional sequence in optimal time so as to minimize costs while maximizing instructional return. Dynamic programming techniques could also maximize time by specifying the level of criterion performance a student must meet in each instructional sequence before he is passed to the next one. A criterion level based on the results of a dynamic formulation could be optimized relative to both the individual student and the whole system, thus saving time and cost. This minimum criterion level would ensure satisfactory performance on both the posttest and in the job setting.

A wider, more encompassing use of dynamic programming would be to monitor the complete technical training system. A dynamic programming formulation for the decision problems could be developed that accounts for the cost of instruction, the gain in competencies as a result of the instruction (setting appropriate criteria), and the assignement of trainees to appropriate training sequences based on differential student characteristics and other variables which are discovered to influence the training attempt. A model could be developed which would control and coordinate all other adaptive models and instructional subsystems. By utilizing proven existing systems, or usable proposed systems and/or procedures within these systems, the dynamic programming model can optimize instruction based on stated goals and existing constraints without a major reworking of instructional strategies.

The ultimate use of dynamic programming technicques in all phases of adaptive instruction requires thorough examination of all existing and proposed instructional alternatives (strategies and resources), all possible student characteristics and learning styles, and the goals of instruction, both desired and mandatory. This major effort should produce specific quantifiable variables which then could be submitted to actual testing in the instructional situation. These experimental results would produce data on which optimization decision processes could be based.

An additional application of dynamic programming in the AIS setting could dynamically control the scheduling of students and courses so as to use the training resources and Air Force personnel most effectively. An individualized instructional system implies that trainees will be completing training at different times. To prevent nonuse of training resources, a scheduling procedure responsive to both the internal instructional system and the external Air Force needs could optimize the scheduling of individual trainee personnel and courses.

Literature Review

A description of recent uses of dynamic programming techniques provides a clearer perspective on their applicability to AIS. As previously indicated, operations research, to which dynamic programming has contributed heavily, can aid in solving industrial problems. Problems such as those of choosing the proper routes for roads, while optimizing traffic flow and minimizing cost, are discussed by Kaufman (1967). Other applications of dynamic programming in decision-making situations include distribution of investments to provide maximum profit, management of warehouse stock, and calculation of optimal storage capacity.

Instructional dynamic programmming techniques having greater relevance to AIS include those of Atkinson and Paulson (1970). Lorton, as reported by Atkinson and Paulson, used these techniques to examine an approach to the optimization of instruction in teaching spelling words to elementary school children so as to maximize performance on a posttest. As described by the Atkinson and Paulson article, the decision problem was to find a choice strategy for achieving the criterion level of performance in the shortest time. Depending upon the model of learning process applied, a method of selecting words to be presented in sublists so as to optimize posttest performance and minimize study time was determined. The method of determining the selection procedure was dynamic in that the history of both the individual and prior students aided in defining the solution. The optimal selection method was shown in each case to be superior to a fixed order of presentation of words.

Calfee (1969) describes an application of dynamic programmming in determining an optimal procedure for presenting paired-associates to obtain criterion performance, while minimizing the number of presentations. In a similar application, Smallwood (1971) considers the cost for instruction as well as the cost of terminating the instruction prior to the learned state. Smallwood's paper develops a dynamic programming formulation for determining the optimum policy for presenting a multiitem list of paired-associate items. This optimum policy for the presentation of the multi-item list can be calculated by considering each item individually and then aggregating the individual results into a total policy. Smallwood suggests that the applications of this method of determining optimal instructional presentation are particularly useful in computer-directed teacher systems that incorporate a sophisticated decision-making capability. He suggests that the complicated computation needed for the initial determination of the optimal teaching policy can be done for many students simultaneously. Then as a new student enters the instructional program, the simple calculations required to adapt the instructional alternative to the student for optimal performance can be quickly performed, producing an instantaneous prescription for the student. Periodically, as more data become available from students having completed the instructional sequence, a complete recalculation of the optimum policy for each item and for the multi-item list could be carried out during off-teaching hours, when the teaching demands of the computer system are relieved. Smallwood suggests that this method of handling adaptation of instruction by computer may result in a more economical system, since the system would now be used more efficiently by trading off relatively inexpensive off-duty computation time for an increased student-handling capability.

Calfee suggests that a simple mathematical model which approximates the learning process is more efficient than a complicated one. This is so because the mathematical analysis rapidly becomes more difficult as the mathematical model becomes more complex. On the basis of the derivation of an optimal presentation technique based on backward induction, Calfee concludes that presenting the item which yielded the maximum immediate gain was an optimal strategy.

Kendrick (1966) suggests that a dynamic programming model could be used effectively for educational planning. He indicates that control theory models are attractive as planning devices because they enable one to specify certain original states of a system, certain desired terminal conditions or targets, and then to search for the levels of the system controls which will produce the desired end result at the minimum cost. He applied the model to determine the number of new students to be admitted to the first level of an educational system every year in order to meet the target levels of the desired number of students completing each level in the system in some future year. Cost factors were also integrated into the model.

Beliman *et al.*, (1966) employed dynamic programming techniques to determine the pathways a psychiatric interviewing situation would take, with the computer simulating a patient. By simulating a psychiatric interview, a multistaged decision process built into the computer can, through optimization procedures, become an adaptive decision process. By building a tree of questions and answers, each with certain assigned probabilities of occurring within the first psychiatric interview, Bellman and his group were able to present a realistic simulation of psychiatric interviewing for training purposes.

Woods and Hartley (1971) report an iterative technique to determine optimum task difficulty in simple computational skills instruction. The goal for the computer-based instructional sequence was for the computer to generate a task sequence by varying the number of rows and the average number size in addition problems. In this way, any particular pupil at any competence level works with any specified probability of success. To accomplish this task, the computer continually re-estimates probability of actual success, generates examples, provides appropriate feedback to the model, makes a continuous error analysis, and stores records of student's progress. The process is dynamic in that decisions of task difficulty are based on the student's past history and present status, the history of other students, and changing goals (that of probability of success).

To provide a basis for the initial stage of the implementation of a dynamic programming model, a suggested list of variables to be considered is presented in Table 3. The student characteristic variables are each presented with the interacting instructional variable as shown in at least one aptitude-treatment-interaction research study.

TABLE 3.

Student Characteristics and Task Characteristics

Student Characteristics Learning and Types	Instructional Task Characteristics	Researcher
Short-term memory	PI step size	Furukawa, 1968
Scientific interest, anxiety level, introversion/extroversion	Inductive/deductive, meaningful/arbitrary	Tallmadge & Shearer, 1969
	Massed/distributed practice (spelling)	Fishman, Keller, Atkinson, 1967
	Overt/correct correction response	Suppes, Ginsberg, 1962
IQ, reading comprehension	Pacing, prompting	Gropper, Kress, 1965
	Placement of review	Gay, 1971
Associative memory, Induction, General reasoning	Expository/discovery (rule application)	Dunham & Bunderson, 1969
	Example/negative example (concept learning)	Tennyson, 1971
General reasoning	Expository/discovery	Merrill, 1970
General reasoning, Anxiety	Expository/discovery	Merrill & Towle, 1971
Anxiety, Active/passive learners	Sequencing	Gallagher, 1971
Anxiety	Feedback, stress	O'Neil, 1970
Anxiety	Test item difficulty Sequencing	Towle & Merrill 1972
Anxiety	Test item difficulty sequencing	Munz & Smouse, 1968

TABLE 3. (Continued)

Student Characteristics Learning and Types	Instructional Task Characteristics	Researcher
General reasoning anxiety, dependence/ independence	Expository/discovery rules, objectives	Merrill, Kalisch, Towle, Steve, 1972
General reasoning anxiety, dependence/ independence	Expository/discovery rules, objectives	Kalisch, Merrill Towle, Steve, 1972
General reasoning anxiety, dependence/ independence	Expository/discovery rules, objectives student/program control	Towle, Steve, Merrill, Kalisch, 1972
n Achievement, n Affiliation	Incentive	Atkinson & Reitman, 1956
Opinion, educational level	Type of argumentative program	Hovland, Lumsdaine Sheffield, 1949
SES, parent education	high/low interest	Marshall, 1969
Introversion/extroversion	Blame/praise feedback	Thompson & Hunnicutt, 1944
Level of achievement	Praise/reproof/neutral feedback	Van De Riet, 1964
Inductive & deductive reasoning	Verbal inductive/ verbal deductive	King, Roberts & Kropp, 1969
Anxiety (AAT), Sex	Constructed response/ no reinforcement/ reading	Tobias & Abramson, 1969

Though the literature produces limited applications of dynamic programming to adaptive instruction, the applications cited indicate that dynamic programming does have wide applicability to the area. Coupled with a high-speed computer, dynamic programming formulation of adaptive instructional procedures and policies could be employed to serve thousands of students engaged in amny different instructional tasks. By utilizing optimizing techniques, such as those that dynamic programming provides, the value of any one instructional segment or procedure is never in doubt. In addition, the optimizing procedures will prevent a situation of greater demand on the resources than can be handled at any one time.

Variables

As indicated in the preceeding paragraphs, a dynamic programming model can be employed to combine and coordinate other models and system. Dynamic programming approaches used within an adaptive instructional model must include all variables which are germane to the proposed submodels and subsystems, the ineteraction and flow of these variables in an instructional-course unit, and the allocation and monitoring of resources (including money and time).

All variables which are to be included in adaptive-optimization procedures must (a) be quantifiable, and (b) have an underlying continuous distribution. Furthermore, this underlying distribution must be given a sufficient chance to be reflected in the data. The effectiveness of any adaptive model is dependent on the quantification of the whole system and the sensitivity of the measuring instruments employed.

This quantification is most difficult in the area of goals and goal statements. Not only must minimal and maximal values be specified for any output, but the relationship of any variable to all other variables, at all possible values of all variables, must be interpretable at each decision point. The problem of visualizing and following all these variables and their interactions so as to formulate an optimal solution (in terms of goal statements) is beyond human capacity. Therefore, the conceptualization of the problem (both the delineation of the variables and the interpretation of these into statements) is mathematical in nature and necessarily computer-based.

The decision about whether to use a dynamic programming approach at all is a relatively simple question compared to the one which deals with the degree to which it should be used, and the energy and funds avaiable. After extensive research and planning, a dynamic programming approach can be divided into a number of categories, with each category implying differing amounts of commitment and implementation at different times. The nature of each category, and what payoffs can be expected from each, is looked at in the following breakdown. The categories differ in (1) the sequence that are first dealt with, (2) the amount of initial commitment of each, (3) the amount of payoff that can be expected from each, and (4) the implications of exclusion and inclusions of differing combinations of each.

An explanation and an elaboration of the categories and functions outlined in Table 4 and Figure 12 follow:

Function 1. Generating the initial adaptive model–including the decision model. Because this initial procedure is germane to the development of any system and its formulation affects the choice of latter functions of dynamic programming, this implementation function is discussed in detail in a following section.

Function 2. Updating algorithms as new performance schedules become available. Updating an algorithm is the first part of a two-step process. The regression equation will first yield a more accuiate prediction of the dependent measure (*e.g.*, scores on Criterion Test No. 4). It will then be decided how this improved prediction affects the goals of the system (of which a specific algorithm-regression equation is but a small part). The improved prediction from an updated algorithm may ultimately lead to better mastery for all students (accuracy goal optimized), less time to a mastery level for most student (speed goal optimized), or elimination of some remediation loops, instructional alternative pathways, decision points, etc. (money or resource allocation goals optimized). The actual decision will be reached from the set of recursive equations derived earlier from the goal statements.

TABLE 4.

Categories and Functions of Dynamic Programming Approaches

Category	Function
1. Implementation	Generating the initial adaptive model
2. Updating & Refining	Updating algorithms (regression equations) as new performance schedules become available.
3. Incorporation	Incorporating new variables into the preexisting algorithms (regression equations).
4. Adapting & Adjusting	Changing the model as a function of changing goals (priorities) and major resource allocation changes.
5. Scheduling	Generating a formulation which optimally estimates the frequency one should use the updating and refining (Function 2). And how often one should attempt to incorporate new variables into preexisting algorithms (Function 3).

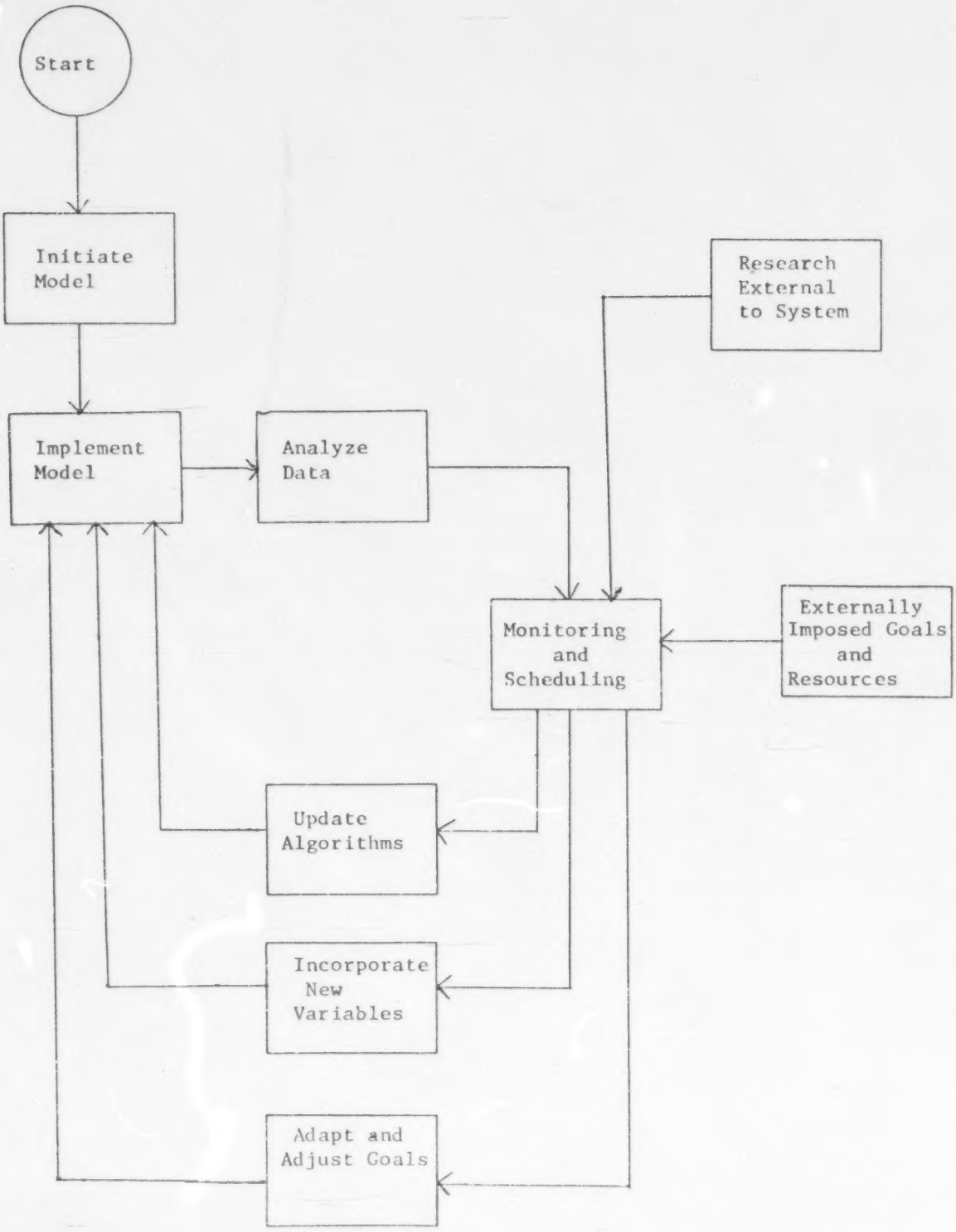


Fig. 12. Categories and Functions of Dynamic Programming Approaches.

Function 3. Incorporating new variables into pre-existing algorithms. This feature may be a result of new money to look at old ideas, or new research findings, or new ideas from empirical data generated by the system itself. Most typically, a new variable (*e.g.*, a premeasure or a criterion test score) will be included in the existing regression equation. Data compilation and analysis will then follow to determine if the variable's inclusion can contribute to optimizing the achievement of present goals. Unlike the updating algorithm stage, this stage is heuristic in nature and parallels the process of setting up an original algorithm.

Function 4. Changing the model as a function of changing goals (priorities) and major resource allocations. If all possible ways that a student can go through an instructional block are considered a series of pathways, then each vertex is a point at which a decision is to be made in assigning a student to the next pathway. Each student will then follow a particular path (*i.e.*, series of pathways) through each instructional block. What is suggested here is a change in the number of decision points as a function of major changes in criterion performance levels, course content, resources (amount of funds, number of instructors, phasing out of equipment), and general level of competence of students.

The repercussions of such major changes can be dichotomized in the following way: (1) disregard the model totally and begin again at Function 1 or (2) build the system so as to allow shifting goal statements and permanent shifts in student and allocation variables. This second approach is the only sensible, viable one for two reasons. First, any model which costs so much to conceptualize and set in motion cannot be scrapped because of minor external fluctuations. In a sense, the system must be externally dynamic as well as intrinsically responsive to the variables fed regularly into the system. Second, optimization procedures can only be effective within a fairly stable framework of goals. Dynamic programming approximates, over time, an optimal solution. Therefore, if the stabilization of content and/or goals cannot be guaranteed or defined for an extended period, attempting a dynamic programming solution to the adaptation of instruction (and the systems approach itself) is probably a waste of time and money.

At this stage of conceptualization, it is difficult to forsee how the model can be expanded (as in Function 3) or condensed by any other method except adding or subtracting one decison point (*i.e.*, set of pathways) at a time and evaluating the consequent effects. One simple way to condense a system would be to delete the least predictive variables and the least efficient pathways. Such a process would be relatively straightforward if the formation of the pathway system was a step-wise, iterative process. Because the cost in administering a scale and including a test or premeasure score in a regression equation is small compared to developing and maintaining different types of media and different difficulty and redundancy levels within a medium, many less efficient pathways would be deleted before any predictive variables would be dropped from the regression equations.

Function 5. Generating a formulation which optimally estimates the frequency that one should update the beta weights (Function 2) and the frequency that one should attempt to incorporate new variables into a pre-existing regression equation (Function 3). The need for the updating and the incorporating functions will decrease as the model stabilizes (*i.e.*, stabilization of pathways, decision points, and regression equations). This stability will conceivably be reached as the number of persons going through the model increases and the number of combinations of new variables and ideas is exhausted. The importance given to the role of this updating and incorporating schedule will for the most part be decided in the formulation of the general system (Function 1). However, its role is also determined by Functions 2, 3, and 4, and the changing quantity of resources allocated specifically to this function.

Structure of a Dynamic Programming Model

It will be remembered that Bellman's dynamic programming principle of optimal solutions to problems emphasizes the interdependence of all decision points. The number , characteristics, and interrelationships of the decision points is a direct function of the goals. As it appears now, a goal statement will be composed of statements of desired mastery levels, of cost-effectiveness of each of the pathways, and of system characteristics (resource and time constraints). The goal statement and the whole system must be in quantifiable terms.

Until a training situation is identified and a goal statement specified, developing an optimal prescription for the student is impossible. In practice, a goal statement can be developed, and a network of contingencies built within those constraints and priorities. Building an optimal solution where there has been no clear definition of goals must take into account every possible goals. At the present, that capability is neither realistic nor desirable.

Implementation of Dynamic Programming Within an Established Functioning Program. Table 5 shows the development of considerations to be employed in a dynamic programming approach to an existing program in which goals have been clearly defined.

Implementation of Dynamic Programming Without an Established Functioning Program. Whereas optimizing established variables and a stable program is conceptually possible, the task of optimizing and developing a program (instructional course/unit) simultaneously given only the goal statements is not presently possible. How many decision points, what kind of variables, what are possible pathways, how do each of these pathways relate to the decision points, what research should be examined–these are too many e'ements to analyze and optimize simultaneously. This can be contrasted with the Air Force training programs and other established programs where the question is more one of finding the best algorithms at each of the established decision points, with each of the available premeasures and criterion measures, and with each of instructional alternatives known to be efficient.

The only realistic approach at present is a simplistic, step-wise, iterative process; one in which programs are first defined and implemented, and then optimization techniques are used as the system take concrete form. There is a large difference between an optimal system and a system that has been optimized. Until a thorough understanding of dynamic programming techniques is gained, the specification of an optimal system in this setting is impossible.

The dynamic programming model is uniquely designed to (a) handle the monitoring of the system; (b) follow each student as he traverses from each instructional unit to the next; and (c) interpret and predict a student's progress at each decision point in terms of the previously chosen goal values. Figure 13 is detailed flowchart of what student pathways and decision points may be included in an instructional course unit.

As the student enters the task condition, his cumulative student profile is available (1. Student Profile Bank). The task requirements, as initially determined by the task analysis, and requisite student skills, determined from data of previous students, are matched with the data in this student's profile bank (2. Basic Profile Requirements). If the student's profile is found lacking some prerequisites, the appropriate remediation is administered (2A. Remedial). The student's success in this remedial program is evaluated (2B. Evaluation), and this evaluative information is then used to update the student's profile bank. The task requirements and the updated profile are then again compared. When the appropriate match occurs, the optimal instructional prescription (3. Instructional Prescription Algorithms) determines the appropriate cost-effective-and-available instructional alternative (4. Available Cost Effective Instructional Alternatives). The student is then given the training according to the prescribed instructional algorithm (5. Training). The effects of this training are then evaluated (6. Evaluation). This evaluative information updates the student's profile bank and provides feedback of the degree of success of the decisions that determined the initial prerequisite behaviors (2. Basic Profile Requirements) and the subsequent instructional prescriptions (3. Instructional Prescription Algorithm). Information from the evaluative stage also determines the appropriate remediation algorithm (7. Post-Training Remediation), if needed. If criterion is met, the next task in the sequence is assigned.

Payoffs

The purpose of dynamic programming is to optimize. Thus, any payoff expected from using dynamic programming will be in terms of the goals that a program designer wishes to optimize and is able to specify in quantifiable terms.

The dynamic programming payoff issue involves (1) consideration of implementing a dynamic programming model for a program (feasibility); and (2) the degree of commitment available for investment, and the amount and kinds of payoffs to be expected (maximization).

TABLE 5.

Stages in the Development of an Optimization Solution in a Preexisting Instructional-Course Unit

1. Conceptual Stage

   -including:

   a. identification and enumeration of variables and levels of these variables

   b. selection of goals

2. Inferential Stage

   -including

   a. collection of subject data from (1) any previous research which has included variables that appear in Stage 1; (2) courses on other programs which have collected or are now collecting data; and (3) pilot studies.

   b. compilation and analysis of data

3. Representation and Equation State

   -inclusion of those variables and those pathways which have been moderately successful up to this point.

4. Optimization Stage

   -optimization of those variables and pathways which were included in Stage 3

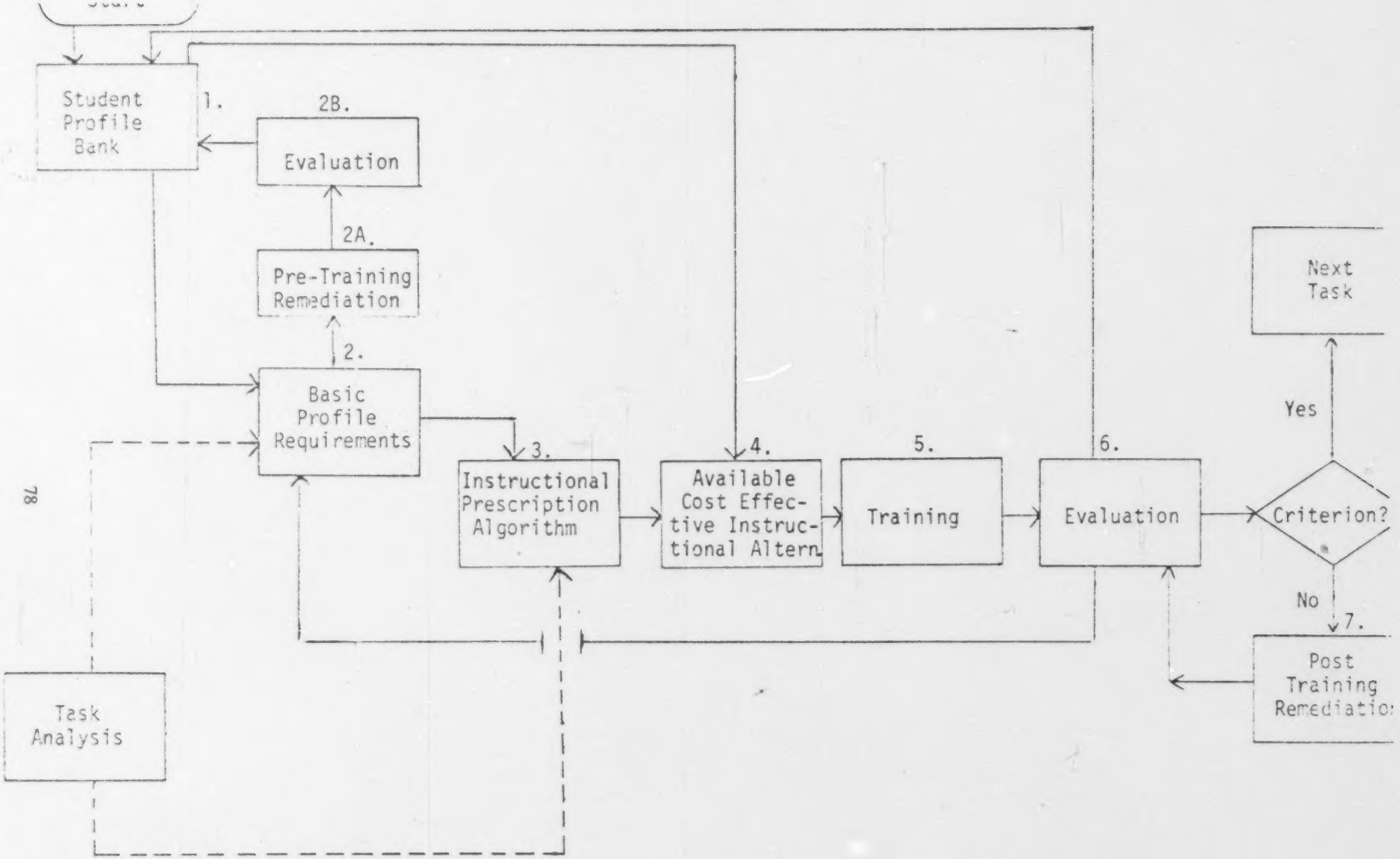


Fig. 13. Adaptive Model Program Flowchart.

Being in a position to decide if dynamic programming is to be used requires a knowledge of what payoffs are to be expected and what kinds and amount of inputs are necessary. It is suggested that a profitable way to view this tradeoff is in terms of payoffs and inputs at each categorical-functional level (Table 4).

Issues and Conclusions

The obvious expenditure of effort and funds to implement dynamic programming techniques at any level in the technical training system requires resolution of several issues before implementation can be attempted. The issues cited in this section are not intended to include all those which influence the applicability of dynamic programming to the adaptive instructional models, but rather are illustrative in nature.

As dynamic programming is best utilized in a complex, multidecision process system, the length and complexity of the instructional sequence will be an important factor in determining the feasibility of using a dynamic programming model to adapt instruction. If it is discovered experimentally that prediction of performance task on an instructional sequence is based on the scores of one pretest interacting with two possible alternatives, dynamic programming would not be appropriate to control the assignment of alternative instruction to students. However, if many student variables are found to interact with several alternatives at several points in the instructional sequence, dynamic programming techniques may be appropriate to optimize the decision process.

In addition, the degree of fine-grained adaptation necessary to produce significantly different results in optimizing on certain prespecified goals will determine the extent of involvement in the controlling/decision-making of instruction by dynamic programming processes. If the decision involves choice of simple dichotomies, dynamic programming probably is not efficient in terms of effort and cost. However, decisions based on variables, each having an underlying continuum, and producing varying degrees of goal attainment, require techniques such as dynamic programming to optimize the decision-making process.

A third issue that must be resolved prior to implementing a dynamic programming model is that of the stability of subject matter within the instructional sequence. Dynamic programming processes require iterative calculations of solutions to recursive equations based on data gathered over many students and, therefore, over time. The data collected must be of the same kind; that is, from the same test items, same instructional requirements, etc. Therefore, if the subject matter is still undergoing revision, data on which optimization procedures is based would not be from a replicated instructional sequence.

A most important issue to be resolved prior to implementing dynamic programming is that of quantifying all variables, including goals. As these optimization procedures require the solutions to sets of recursive equations, all variables in the equations must be in the form of mathematical quantities. It is this determination of a quantification scheme that initiates the ordering and assigning values to goals, which is the basis for the solution of the optimization equations. Most other input variables will be in terms of a test score, or some other easily quantifiable characteristic which will readily fit into the recursive equations for solution.

Though other issues will be met, the last to be mentioned is that involving the updating of the decision process. As this updating and revision requires the solution of recursive equations based on data collected continually to provide decisions responsive to the system and personnel, the issue of how frequently and on what basis will the updating be processed should be faced. The inclusion of new variables emerging from research versus the stability of the instructional decisions will have to be weighed and appropriate guidelines developed. Issues regarding the cost of the solution of new equations, possible changes in necessary resources, changing goals, changing constraints, etc. must be resolved, and provisions for the accommodation of such changes built into the decision-making system.

Recommendations

The following recommendations are made:

- Though the requirements of a dynamic programming model of adaptive instruction are demanding, the benefits accuring from such a decision process appear to be great. The inclusion or exclusion of variables are based on empirical data which then can be examined in the light of optimization of prespecified goals. Decisons in the form of prescriptions for instruction are also based on optimization of goals. The administrators of the training system are assured of decisions which will produce optimal results in student performance, system time, and overall cost. Therefore, it is recommended that the AIS project develop a dynamic programming model. This development will require extensive research and development efforts.
- The development of the dynamic programming model should be phased as follows:
  - Initial system description
  - Single variable optimization studies
  - Multivariate optimization studies
  - The emergining of cost-effective criteria and decision processes with the evolved dynamic programming model.
- Each of the AIS course operations could profit from the application of a dynamic programming model. This is especially the case for PME and Weapons Mechanics in that the model would provide for optimal utilization of expensive high-fidelity simulators and trainers.
- It is recommended that the dynamic programming model be both inclusive of other models and focus on the optimal utilization of AF training resources.

VIII. NATURAL LANGUAGE MODELS

Natural Language Processing (NLP) research began in the early 1960's in an attempt to develop computer systems which could carry on conversations with people and answer inquiries. As reviewed by Pirotte (1971) and Simmons (1971), these efforts have been fairly successful within a constrained dialogue environment. More recently, as reviewed in the following paragraphs, investigations have been made to utilize NLP for training and counseling purposes. Table 6 provides characteristic examples of some possible interactions between the student and system within an AIS context.

Characteristics of the NLP Models

Several characteristics of NLP have become clear in the context of adaptive instruction. The first is that NLP usage is inherently adaptive because the students' knowledge, mental processing, and language capabilities must be modeled and taken into account in order to achieve an appropriate system response. Second, the NLP task determines both what the student is expected to do and what he will do, since the task characteristics are embedded in the conversational dialogue (*e.g.*, a new definition or a new interpretation are presented for both naturalness of dialogue and achievement of the task). Finally, the interactive dialogue occurs within successive contingent language statements that clarify and focus the mutual student-system understanding of and progress toward the training goal. Any adaptive model for computer-based natural language interaction must, therefore, account for these three characteristics.

Semantic Memory Models. In order to allow for the characteristics of the students' knowledge and their mental and language competencies, the NLP model to be presented is based upon the concept of semantic memory that is, the model of meaning functions consisting of verbal representation of concepts, properties, and relationships within an organized scheme. For example, given a taxonomic scheme such as vehicles, the semantic organization within the system and human memory can be represted as stated in Figure 14.

TABLE 6.

NLP Dialogue Examples

C. Please state your name, course, and problem.
S. Wallace Mechner, weapons mechanic course. I wanted to find out about what I can do after the course.
C. Do you mean advancement in your Air Force career Wallace?
S. Yes, like more schools and changing to another field.
C. As you may know, the Air Force has one of the largest educational programs in the world with vocational/technical training, and completion or advancement in both high school and college. In addition many speciality schools exist. If you have a particular area of study in mind we can talk about it. Of course, much of what can be available to you depends upon how well you do in your present assignment. I see by your course records that you are progressing very well. Keep it up.
S. I enjoyed the basic electronics lessons and would like to get in that area.
C. ....

(C = computer and S = student)

C. Please state your name, course, and problem.
S. Irving Mannix, Inventory Management. I completed all of my work early so far to have extra leave time but now I need money and want to know if I can change my request to get proficiency pay.
C. Well, as you may know from the orientation session not all sections have leave time or proficiency pay as advantages for early completion and the two are not directly interchangeable. However, it is not too late to change your request. I can tell you how to do that if you wish and we can discuss the proficiency pay scale too.
S. I want to discuss the pay scale.
C. O.K. The following blocks have pay incentives in addition to the overall course time....

C. Please state your name, course, and problem.
S. Peter M. Elroy. Precison measuring equipment. I am having trouble with the block on vacuum tubes.
C. I see that you have been successful up through the third unit in that block but failed the tests on solid state circuits in unit 4. Do you think you have had sufficient time to study for this?
S. Yes, but I still don't understand it.
C. How did you do on the workbook?
S. Most of the problems threw me and I had to ask others what they did.
C. By "threw me" do you mean you didn't understand the question or how to arrive at the answer?
S. Yes.
C. Well, I would like you to take a little diagnostic examination. It is defining terms and will help to pinpoint your problem more. Sign on to DITES3 and them come back to me.

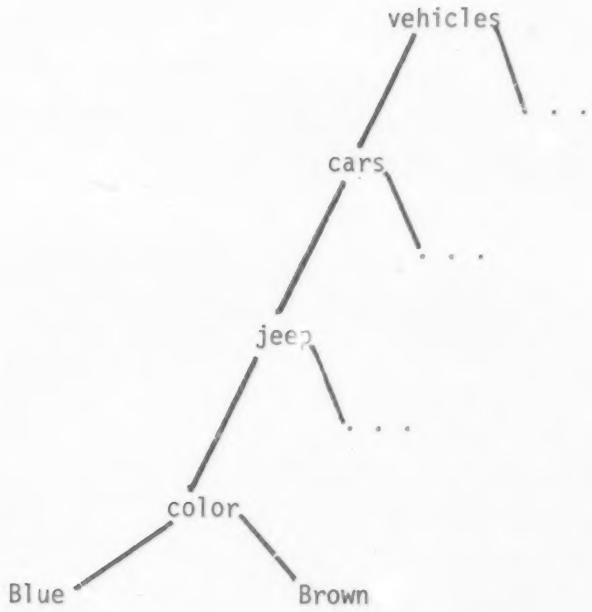


Fig. 14. Semantic Memory Model.

The semantic relationship for the concepts (names of classes), the concept properties, and the relationship between concepts is specified by this hierarchical organization, that is, it can be derived that all cars are vehicles, that Jeeps are blue or brown, and that Jeeps are cars. Given a setting where the purpose is to instruct a student in this taxonomy, the interactive dialogue could be shaped in precisely this organized way. After accomplishment of the terminal objectives, the student would likely have this material organized within his memory in nearly identical structure. Therefore, the NLP system would be modeling the student's memory structure and processes.

Operational Processes. The NLP model as implemented in the computer represents processes essentially similar to a reader who is attempting to comprehend a passage or a listener who is interacting with another human in a dyadic context. As the student inputs a verbal response (usually typed), the NLP performs a pattern-operation transformation on the input (Simmons, 1970). The first step in the pattern operation consists of searching for a given language pattern in the input. This leads to identification of key words, phrases, or sentences (sentence decomposition processes). Parsing techniques may be employed. Parsing is a syntactical analysis process by which the parts of speech are identified. When a key pattern is found, a response generation process associated with the key pattern is invoked so that part of the input is grammatically combined with a partially composed sentence so as to output the system's response sentence.

To enhance the sophistication of NLP procedures, additional sentence decomposition elaborates would be implemented. First, the pattern-matching routines can be guided by semantically controlled parsing procedures. Secondly, the order of key words, phrases, and sentences matching can be structured by the previously noted location in the model's semantic memory. This leads to hierarchical decomposition analysis by semantically contingent processes that facilitate response recognition and speed.

Role of the NLP Models in AIS

NLP is an optimal technique for encouraging and eliciting verbal knowledge and judgment responses from students. For this reason, NLP is an excellent potential tool for evoking and evaluating complex concepts, judgments, and critiques. These are especially useful in counseling applications, the primary NLP application proposed for AIS.

The five content areas of AIS counseling are (1) the incentive management process, (2) career aspirations, (3) high-frequency learning problems with solutions, (4) student critiques of instruction; and (5) special motivational training. Counseling within the *incentive management process* may consist of dialogues about interpretations and implications of incentive schedules as previously presented by narrative materials describing the incentive programs in each course. *Career counseling* may be provided on an interactive basis whereby the student queries a data base (semantic memory) which will respond with career ladders; for example, a student's future in the Air Force can be handled in this manner. As high-frequency *learning problems* are identified within each of the courses, the student can be given an opportunity for natural language dialogue concerning the nature of the problem and potential solutions found successful with other students. In addition to the usual student *critique rating* forms, a natural language dialogue concerning the student's perceptions of the strengths and weaknesses of various aspects of the course could be collected systematically within these NLP counseling sessions. Student-generated comments on both the courses and his training experience at Lowry Air Force Base could be collected in this manner. Finally, for those students in need of special *motivational training* (*e.g.*, need achievement training), the couseling time can be utilized for the presentation and interaction of special motivational training materials.

AIS Payoff

By handling the counseling process by computer and on an as-desired basis for each student, one may expect that not only the usual initial orientation for such areas as career and incentive counseling may be shortened or deleted, but also that resource people (instructors) may be less burdened with standard, repetitive discussions with each student.

As a second area of payoff for the AIS, each student will have immediate access to a resource for solving problems. They will not have to rely on peers, or wait until instructors or Air Force documents become available. This will result in a third payoff in that it can be anticipated that students will be less likely to experience mounting interference in learning caused by unresolved counseling needs. Students often spend unwarranted time thinking about such problems until their resolution.

A fourth area of payoff to the students would be the enhanced problem-solving and information acquisition due to informal characteristics supported by the use of natural language. These characteristics reduce the formal and semiartificial setting for the counseling sessions which would be necessitated by a standard techniques. The "natural" approach not only allows for faster, more efficient problem-solving and information acquisition, but it also provides for reduction in the restraints found in traditional counseling situations. Smith (1963), Evans and Miller (11969), and Cogswell and Estavan (1965) have found that more candor and honesty were evident in computer-based comment acquisition systems than in personal interviews. Therefore, NLP approaches to counseling and associated dialogue requirements have high payoff potential.

Review of the Literature

Attempts to develop NLP systems for educational use began in the late 1960's (Simmons, 1968; Feurzig, 1969; Taylor, 1968; Tiedeman, 1968; & Carbonel, 1970). Most of the efforts in this area focused upon the problem of general analysis of language to determine intent and meaning; *i.e.*, to develop a computational model of verbal understanding. However, as work progressed in instruction, testing, and counseling, the student and the system were dependent on the objectives and strategies of the task. All factors important to the success of the NALP systems in an educational setting had to be integrated into the system itself.

More specifically, the emerging research problems became the following:

- How can an educator input to an NLP system the specification of decision-making for strategies and content of conversation when the student is conversing with freely constructed language?
- How can the student's characteristic be taken into account so that his verbal replies may be properly analyzed and responeded to fully?
- How can the educator control the conversational flow on some systematic basis and evaluate the interaction for its effect according to educational objectives?

The literature review is intended to show how the use of a semantic memory as on NLP data can be utilized to address these three problem areas. After a discussion of current projects, the review turns to the empirical and conceptional basis for a semantically based NLP model. This includes the research on semantic information processing, hierarchical organization of memory in both people and computers, the concept of subject matter maps as related to semantic models of memory, the use of student maps of memory, and the student expectancies in a natural language dialogue. All of these allow derivation of a model which allows specification and rationale for the NLP adaptive model.

NLP. Three current projects are discussed in this section which are considered to represent the best approaches at the present time. The first of these is a system called Protosynthex III. This project was begun at System Development Corporation, and it is being developed further at the University of Texas by R. F. Simmons (Simmons, 1970; Simmons & Burger, 1970). This effort is representative of the other two efforts to be discussed in that it depends upon a semantic network for its capability to converse. In Protosynthex III, this network is used to generate semantic equivalents to student inputs. The tutorial decison model for Protosynthex III has a correct answer to a question in its data base, which has been formulated by an educator to contain only the necessary and sufficient information to answer the question. This answer is called the Canonical Answer (CA). The Student Response (SR) is taken by the language processor and checked for semantic equivalence to the CA. This process allows for determination of exact sufficiency, excess detail, insufficient information in the answer, and correctness of the answer. The exact model consist of a 5 X 4 matrix in which one axis describes the degree to which a student's answer semantically matches exactly, partially, overly, not at all, or incorrectly, the answer in the data base. The other axis describes correctness, relevance, feedback type, and the decision pertaining to the answer. Given a case on the first axis, one may derive the proper information for the second axis. For example, a student who ansers with totally incorrect information may be considered incorrect and irrelevant and given negative feedback with a remedial response. Thus, the tutorial decision allows for system responses to conform to the correctness and relevance of the student response.

A second project, SCHOLAR, has been implemented at Bolt, Beranek and Newman, Inc. based upon work of Jaime R. Carbonell (1970). SCHOLAR also uses a semantic information netework as its data base. In a directed graph tree structure, the information units point to other subsuming facts, properties, and relationships. The resulting hierarchy can be searched both in terms of meaning matching and relevancy by consideration of the depth of search; that is, if a student is asked a question, it is reasonable to anticipate his answer as Simmons has suggested for Protosynthex III. If, however, students are allowed to ask questions, as in SCHOLAR' the relevant responses to their questions must be anticipated by rules which state the relevant level of search in the semantic tree. This is one of the most important problem areas for SCHOLAR. Another way of stating the problem is, "what is relevant as well as correct information for responding to a studen's query?" For example, if a student in the AIS context asked about incentives for early completion of the Inventory Management course, it would be helpful to respond with "added leave," but not with "promotion." While promotion may be part of the incentive system, it would not necessarily be suggested for early completion of the cours. Therefore, it would be inappropriate as well as irrelevant to the query. The decison-making for SCHOLAR proceeds on the basis of weighted and arbitrary rules constrained by context rules. These context rules provide the order and string size utilized in the decomponsition process.

The final project to be discussed is being developed at Florida State University. Recognizing the problems of decision rules for relevancy and content, FSU staff members have been working to implement a systematic method by which educational objectives could be formulated for NLP, and conversation flows could be controlled and prespecified by strategies of the course instructor. This effort has been based upon the work of Quillian (1967) and the current research concepts of human hierarchical memory organization. Basically, the technique requires one to specify an expected hierarchical organization of some subject matter through which a student may proceed level-by-level, in level increments, and in ascending or descending order. By task analyzing the subject matter in terms of an expected memory organization, one hopefully will be able to structure the data base so as to restrict irrelevancies and incorrectness of the dialogue. Thus, this is basically a systems analytic approach with a task analysis of expected memory organization.

Finally, while not based on semantic networks concepts, one of the most appropriate NLP projects is the Information System for Vocational Decisions (ISVD) which is a computer-based system for providing career guidance. The project is a product of several members of the Harvard Graduate School of Education (Tiedeman, 1968; Ellis & Tiedeman, 1968). One of the goals of the project was to allow an inquirer to make career decisions by obtaining vocational information from the data base. The inquiry was to be in the inquirer's natural language since this reflected his internal world (Ellis, Pincus, & Yee, 1968). In 1969, the ISVD project added an additional dimension in that the system was to be studied for explicit instructional usage (Roman, 1969).

Semantic Networks and the Organization of Student and System Memory. Semantic networks were introduced as a basis for NLP by Quillian (1966, 1967, 1969). A semantic network is essentially a data base of facts, concepts, and relationships which, by its hierarchical structure, defines and gives meaning to words in terms of other words. Quillian uses the analogy of a dictionary in which definitions contain words which, in turn, may be looked up to further delineate meaning. This process may continue until all words are accounted for in terms of other words, resulting in a hierarchy of concepts, properties, and relationships. Quillian considers such a model of meaning as useful not only in an NLP setting, but also as a model of human memory. Collins and Quillian (1969) have, in fact, tested some of the assumptions of the hierarchical nature of the model and found them to apply to humans in a retrieval task.

Mandler (1967, 1968) has also addressed the organization of human memory in terms of a hierarchical scheme. On the basis of Miller's (1956) concept of chunking, Mandler has concluded that people organize information classes in sizes of 5 ± 2 information units. Because of the limits on intake of information, people must chunk or reclassify; when too much information is available for input, subclasses or new chunks must be generated. This allows the following three principles to be stated:

(1) Organization is a necessary condition for memory;

(2) The organization of verbal material is hierarchical; and

(3) The storage capacity within any given category is limited, thus necessitating subcategories which are also limited.

Mandler's studies have generated a great deal of research on how people organize verbal memory. Wortman and Greeberg (1971) further investigated verbal memory by looking at the recoding process performed by a student when given a specified organizational scheme. They found that a student must (1) perceive the specified organization of categories, (2) chunk within superordinate categories, and (3) establish the hierarchical relationships between superordinate and subordinate categories. This actually specifies the components of the organization process suggested by Mandler.

One of the issues discussed by Mandler is of particular importance for the context of the adaptive NLP model, namely, a specific organization which is helpful or hindering to a student. Mandler suggested two strategies for organizations: a priori experimenter structures as opposed to subjective organization. A student's subjective organized memory seems vastly superior. Bower (1969, 1970) has suggested a similar process in order to retrieve information from memory. Information may not be retrieved unless so organized. Given the storage limits on categories, Wood (1971) has investigated the effect of forcing reorganization of memory information units and found significant negative effects when forcing two or more category reorganizations. Therefore, the NLP model should allow for individual organizational entries of categories and relationships while maintaining the necessary and sufficient relations among concepts as viewed from training objectives.

Subject Matter Maps as Semantic Networks. Seidel (1969, p.3) has suggested that the subject matter for any instructional use must be organized in a manner which will provide "the decision model with a basis for deciding which factor, principles, or procedures are built on which other facts, principles, or procedures, what interrelationships exist among them, and which topics may be presented before or after which other ones." Seidel suggests that, without such a map, an instructional decison model cannot tell where it should start, what the next step may be, and how to arrive at a terminal point. This concept of a subject matter map is conceptually equivalent to an expected student memory network. The decision model would consist of the rules for interaction between the subject map and student. Thus, the NLP model should consist of both a subject matter map based on memory organization adn the rules of interaction for the map.

Student Maps for Semantic Networks. It is obvious from the previous discussion that any form of NLP interaction is dependent upon the student organization of memory. This necessitates the recognition of a student classification and organization scheme. A student map and a description of the instructional flow during student interaction with the system may be used to highlight the similarities and differences between the student's organizational structure and that designed into the instructional program. This includes noting the lack of organization and absence of information within the student's memory. Schank (1971) has suggested that people interact in an NLP or human conversational setting on the basis of several modes of expected context, ranging from societal norms to individual preferences. While Schrank's expectation classifications are not particularly operational, they do point out that a student map of interactive flow must take into account different possible contexts or orientations of the student which mediate and determine the memory organization. The student map is that operational part of the model which provides for context and meaning.

Counseling Expectancies. Ellis and Tiedeman (1968) in the ISVD project have suggested that expectancies for students in a vocational counseling setting are based upon the early states of the decision-making process. This concerns the need to acquire information with which to clarify choices and to plan for alternatives. During this period, a student must relate the information to personal attitudes and feelings. This may be considered Schank's expectancy, and relates to a student map in that a given flow through an NLP interaction should provide a picture of the student's exploratory state and direction. In this early state, the decision rules model must use the student map to determine the information needed by the student.

The Counseling Process

As viewed here the counseling process consists of the task characteristics, the decisions, and the information-processing a student may utilize.

Task Characteristics. Tasks in a counseling situation are seen to have two basic characteristics. The first is that of information dissemination. That is, given that a student is looking for incentives or career possibilities, he must be given information regarding career choices and their contingencies. Incentive and career counseling are seen as being more directly dependent on information dissemination than the other forms of counseling discussed previously. The second mode consists of motivational presentation of an intrinsic nature that will affect the basic drive processes of the student (*e.g.*, need achievement training). The information for these two types of counseling modes should be relatively more organized and complete. Further, the subject matter has an inherent organization, both hierarchical and categorical, which lends itself rather well to subject matter mapping.

Counseling for motivation and learning problems, on the other hand, may be more a matter of memory reorganization and coherence than pure dissemination. While information is being presented, the dialogue engenders motivational and learning problem conflicts with the idealized learner as represented in the program. Thus, memory reorganization is undoubtedly critical. The student mapping and decision rules must reflect this expectancy on the part of the student. That is, the interaction will occur in the presence of a conflicting predisposition within the student.

Decision—What and How to Present. Bellman (1971) in investigating interviewing techniques, has identified two basic types of decisions which are useful in the NLP context. The first of these is a one-stage process in which decisions are made on the basis of only the previous information unit. The more typical decision process is a multistage process in which a sequence of decisions over time or contextual sequences are involved. Time is seen as the prime parameter.

The initial interaction and much of the information dissemination in the counseling process are viewed here as requiring one-stage decisions. For motivational and learning-problem tasks, multilevel decisions would involve the model's decision rules which associate a student map with an information unit in the content map. Further, the multistage process is essentially iterative and requires continuous adaptability over time in terms of student map. It is in the consideration of a multistage decision process using rules which associate student maps with content maps that the NLP model becomes cybernetic.

NLP Model Structure and Variables

Figure 15 provides a schematic representation of the proposed model. Processes 1 and 2 represent the activities which are part of the instructional systems analysis for NLP as used by the Florida State University project, described earlier. The result is a subject content map organized as a semantic network (Process 3) which is related to educational objectives. This network is the basic content for presentation to the student such that the student may interact meaningfully (Process 4). After eliciting a student response, it must be analyzed to determine word and phrase classes (Process 5). This is done in order to allow determination of semantic equivalance and may necessitate use of the semantic network. No actual correctness, relevance, or meaning is attached to the response at this point. It is through Process 6 that these determinations are made by the set of decision rules. The rules model also check prior history from the student map (Process 7) and chooses the next presentation according to the semantic network. At the same time, the student map is updated.

This is the structure of the model. The three main determiners of the model are Processes 3, 6, and 7; subject content map, decision rules and student map, respectively. It is within these three general classes that variables may be derived.

Given the nature of the content maps, student maps, and the counseling process as discussed in the previous paragraph, the design variables for the model can be identified as content, student, and decision-oriented group clusters.

Content. The organization of subject content maps must be based on the task. Three prime sources dictating organization exist. First available materials which may be utilized by students prior to NLP interaction will have an existing organization and must be considered. Second, the emphasis on information units by the educational institution should be reflected in the defined objectives that effect the NLP organization (for the AIS, this is the ATC and Air Force, in general). Finally, the expectancies and predispositions of students must be utilized in order to optimally organize content.

These, along with the actual subject content, may be combined in an analysis according to hierarchical organization by concepts, properties, and interrelationships. These are the input variables with the output variables being the content map.

Student. The student map generation differs from the content map in that it is developed during the interaction whereas the content map is developed prior to interaction. The student map acquires data on each student's flow through the content map. Information must be acquired during this flow which includes the following: the network modes passed through, the next mode chosen, the noting of missing or incorrect information units for the student, and the noting of inappropriate student organization according to an objective. The student map thus provides the data for multistage decisions.

Map Flows. The counseling process includes all of the decision rules which must be included in the model to relate student maps to content maps. The one-level decisions need only note the student map for the immediately preceding event. The multilevel decisions must be based on rules noting more of the student's map. The actual decisions made and the strategies used are a function of the objectives, the content, and the students. For example, if a student incorrectly responds to a question concerning the relationship of two concepts but has correctly used the concept names previously, it would be desirable to establish that relationship for the student as the next step. If, however, the student has not gone through a flow which required the correct naming of one or more of the concepts or their properties, these must be the next steps according to the hierarchical organization principles.

Recommendations

Three areas of recommendations may be noted. These are relationship of the model to NLP systems, training for use, and validation. In order to implement such a system, the following three items must be considered:

- Model Relationship to NLP Systems. The model has been developed with the consideration that it would be desirable to embed it within current or future NLP systems. This goal has been achieved to the extent that the model may be implemented within any NLP system regardless

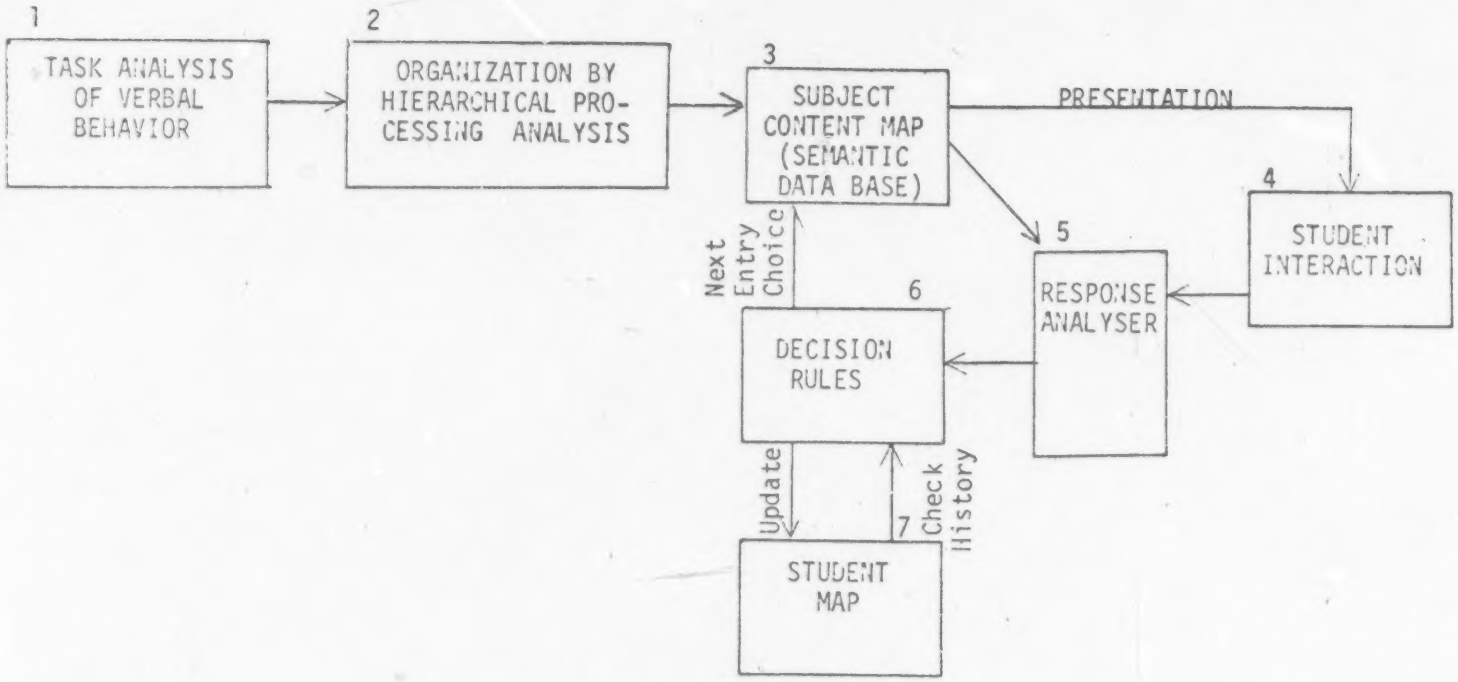


Fig. 15. NLP Adaptive Model Flowchart.

of the techniques used in response analysis. Any given NLP system is represented in Figure 14 by Process 5, response analysis. Two major orientations are used currently in response analysis for NLP–syntactic and semantic analysis. The present trend favors a semantic analysis approach, although a few years ago, pure syntactic analysis was considered of prime importance. In fact, some current researchers are of the opinion that semantic analysis is both necessary and sufficient (Hays, 1967; Quillian, 1967). If syntactic analysis is utlized, the result of the analysis is fed directly to the decision rules processor. If semantic analysis is utilized, the semantic network should be embedded in the larger semantic data base, and the decision rules may then receive the results of the semantic analysis. Thus, the semantic analyzer would use the content map directly.

- The authoring of NLP dialogues has not been sufficiently recognized as a problem in the literature. It is nevertheless a problem directly relating to the specification and evaluation of NLP dialogues. The systematic approach of content mapping discussed earlier is an attempt toward solution of this problem. Any educational implementation of NLP on more than a research scale should provide training in this systematic approach.
- A related problem is the validation of the dialogue system. Several possibilities have been suggested as a result of the work done at FSU. The first is to follow a standard systems approach relating instructional objectives to test questions, and, through the hierarchical content map, to categories or levels of the hierarchy. A pretest/posttest procedure would probably suffice for data collection. The second possibility is to use a sorting or categorization task as the testing situation within the same system approach. This would provide needed information concerning memory organization.
- In respect to the AIS courses, it is recommended that the NLP model be implemented and evaluated, especially in the student evaluation and counseling requirements.

IX. AUTOMATA MODELS FOR ADAPTIVE INSTRUCTION

Characteristics of the Model

The type of model described in this section introduces a theoretical orientation for describing and predicting the *states* of learners. This theory is not new, but, to date, it has been used primarily in disciplines other than the behavioral sciences. Specifically, it has been used in computer science and engineering to study the behavior of complex machine systems. The approach to be described is called Automata Theory. The conceptual basis of the theory allows its application to the study of human "systems."

The word "systems" is crucial to the theory. Automata theory is an approach to the modeling of systems. It is part of a larger theory of systems and is distinguished by its logical and mathematical approach to the definition of systems. A detailed discussion of this basis for defining system parameters shall be provided later. Some of the models thus generated which may have relevance for training will also be discussed. In this section, only a brief characterization of this body of knowledge is developed.

The basic assumption of general systems theory, as applied in the engineering professions, is that any physical device can be represented functionally in terms of relations between three types of variables which describe input, output, and the state of the device. This is the general paradigm for a system as illustrated in Figure 16.

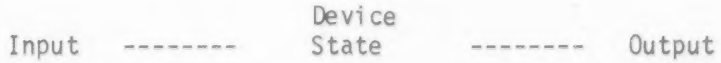


Fig. 16. General Paradigm for a System.

The hope seen for adaptive modeling utilizing automata models is for the development of a technique that is sufficient to handle the many complex tasks which elude current instructional models. Automata theory, with its core requirement of state representations, lends itself reasonably well to such tasks. Consider, for example, the task of electronic troubleshooting. This capability is paramount for good electronic technicians and required in many technical courses and jobs in the Air Force environment. The criteria for what makes a good troubleshooter are elusive. That is, it is difficult to task analyze the situation to specify instructional objectives because the problem-solving sequences are not readily analyzed in terms of performance. One could, however, analyze the task in terms of possible problem-solving states by which a troubleshooter may be viewed. The representation of such states is, of course, the most difficult problem for automata theory and is discussed further in later sections. The important point to be made here is that the state analysis may make a representation of complex behavior more feasible than is currently possible. If the representation is realized, automata models provide a powerful tool for prediction within an adaptive system.

The possible role of Automata Models in the AIS is suggested in the preceding paragraph. It is a futuristic role since much work remains to be done in the area of state representation before an operationalism can be realized. However, given the importance of complex behaviors in many critical jobs in the Air Force environment, the possibility of a more systematic tool to provide more people with the required capability (less failures, less mediocrity, less training time, and, therefore, more on-the-job time) is worth striving toward. In this regard, the payoff is possibly high, although a quantative payoff level cannot be presently ascertained.

Literature Review

Simon (1969) has recently stated the proposition that not only can man be conceptualized as a system, but that: "A man, viewed as a behaving system, is quite simple. The apparent complexity of his behavior over time is largely a reflection of the complexity of the environment in which he finds himself." Simon suggest the example of an ant who, while traveling from one point to another, appears to follow a complex path. However, this seemingly complex behavior is not so much a function of the complexity of the ant as it is of the complexity of the environment through which the ant must travel. It is suggested that the ant actually is operating with very few rules as it detours around hills and follows gullies. Just as a complex machine maybe described in terms of functional components and performance characteristics, so may man. It is possible to identify such functional components as memory, perception (Simon, 1967a), or emotional control of information processes (Simon, 1967b). This is a way in which to characterize human systems for use in an Automata Model. It is the characterization of systems and their device states that is important to automata theory. This literature review is thus oriented toward schemes of system characterization which may be fruitful for training systems.

Background. A naive definition of an automaton might be that it is any object which appears to be self-acting. However, this definition should only be used impressionistically. An automaton, according to formal automata theory, is defined by a rigid logic to be discussed shortly.

Formal automata theory was begun in the late 1940's by a mathematician who noticed similarities between the behaviors and structures of men and machines. John Von Neumann (1959, 1966) over a period of several years developed a theory which he felt could model both types of systems. The basic paradigm for automata theory is the system as described earlier and represented in Figure 16. The processing mechanism between input and output is assumed to be composed of storage and combinatorial logic elements. However, the actual physical structure is unknown, and the prime interest is in the properties of the system and the manner in which it processes information.

Because the system is assumed to have storage elements, the current output depends upon the history of the system. Both input and output may be represented as a sequence of symbols. The system remembers both part of the history of the inputs and responses; this history describes the current state of the system at any given observation. Thus, given the current input and state of the system, the output should be able to be predicted when the system is adequately described because the output depends on only these two factors.

Booth (1967) has characterized the critical problems of automata theory as falling in two categories. The first is that of system characterization. That is, given a system, the characteristics that determine the system's overall behavior must be defined. Depending upon this characterization, any of the two dozen or so currently defined Automaton Models may be chosen. The second problem is that of signal characterization. That is, the information contained in the signal must be prescribed by some relevant combination of the signal properties. Most of the review to follow is concerned with two primary orientations which are currently used to characterize automata within the behavioral sciences–S-R theory and information processing theory. In order to fully understand these theories in terms of automata modeling, a brief discussion of formal automata theory is necessary. Throughout the following text, the basic theme is to suggest appropriate ways of system and signal characterization.

Automata Mathematical Basis. Although Von Neumann did not define the mathematical basis of automata, others have continued toward this end (Arbib, 1964, 1968). The mathematics of automata has taken the form of one of the newer areas in mathematics, That of abstract algebra. This algebra is based on set theoretical notions. One first defines the sets of elements (for instance input and output symbols) to be described. Given the set, the next step is to identify the logically acceptable operations and types of elements for that set. Depending upon the number and types of acceptable operations and the types of elements within the set, one may then identify an appropriate algebraic system which has been defined for that universe of sets. In this manner, the modeling proceeds according to the logic of set theory to the mathematics of abstract algebra. Figure 17 shows the hierarchical progression of algebraic systems which may be used corresponding to different types of sets. Most work in automata theory at present seems to be done at the level of the semigroup. A semigroup has only one operation defined on a set.

As an example, let us discuss an automata which may be particular application in modeling human behavior, the pushdown store. A good analogy to the pushdown store (Hopcroft & Ullman, 1969) is the stack of plates on a spring often seen in cafeterias. The spring below the plates has just enough strength so that only one plate appears above the level ofthe counter. When the top plate is removed, the next dish pops up. If a plate is placed on the top of the stack, the rest of the plates are pushed down. In the same manner, the pushdown store is conceptualized to work with symbols within a system. Symbols may be considered to be on a list. Only symbols at the top of the list may be removed, and symbols to be placed on the list must be entered at the top. When a symbol is entered, the other symbols on the list are pushed down. If the desired symbol to be accessed is, for example, the third down on the list, the first two symbols of the list must be removed. They are popped off the list to retrieve the desired symbol.

More formally, the pushdown automaton is conceptualized as in Figure 18. It consists of an input tape of symbols which pass a read-only head in a sequential manner. There is also an output tape with a write-only head also operating sequentially. Connected to the processor ofthe system is a memory unit which is a pushdown store. Algebraically this system is a semigroup.

Several variations of the pushdown store may be noted. This type of automaton may be a transducer or acceptor. When used as an acceptor, (the input changes the state but generates no output), the automaton may be used in the study of languages. A pushdown transducer (the input is changed by the state to generate an output) used to study memory is described later in this report. The pusdown automaton may be deterministic or nondeterministic. A nondeterministic model is one which allows more than one output symbol for a given input symbol.

Let us further use the stack of plates to characterize the operation of the pushdown store. Suppose the plates are of different colors, say, red and blue. The system may be defined to have rules which stipulate that if a red plate is input and the system is in state q^1, then add a blue plate to the output to change the state to q^2; if the system is already in state q^2, it may remain in that state. Similar types of rules may be defined for other possible situations for variations of input and state combin ations. In this way, the system operation has been characterized insuch a way that the output for a given string of input symbols maybe predicted.

The next such section describes the actual use of a pushdown automaton model for psychological processes.

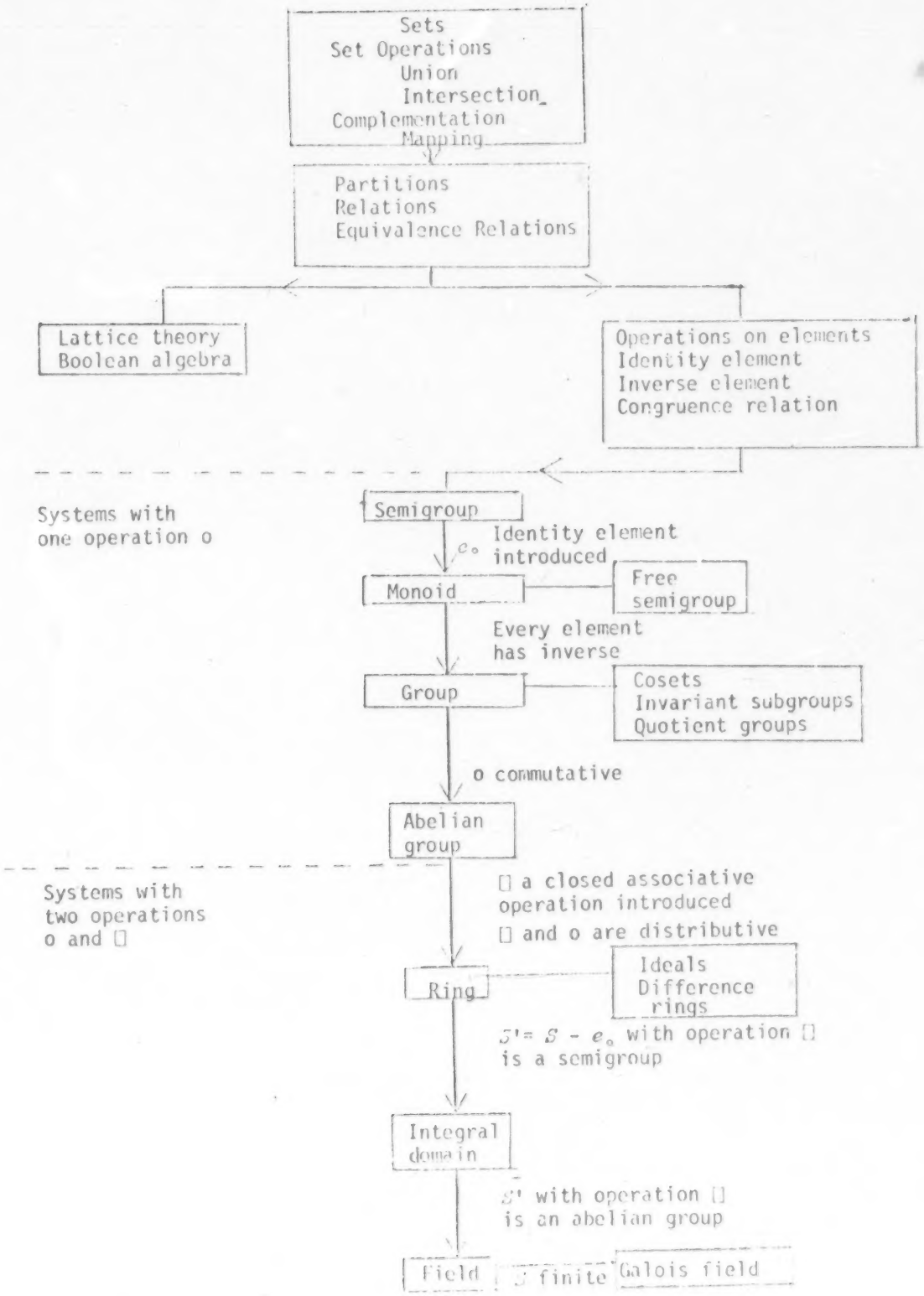


Fig. 17. Block Diagram Illustrating Interrelationships of Different Algebraic Concepts From Booth (1967).

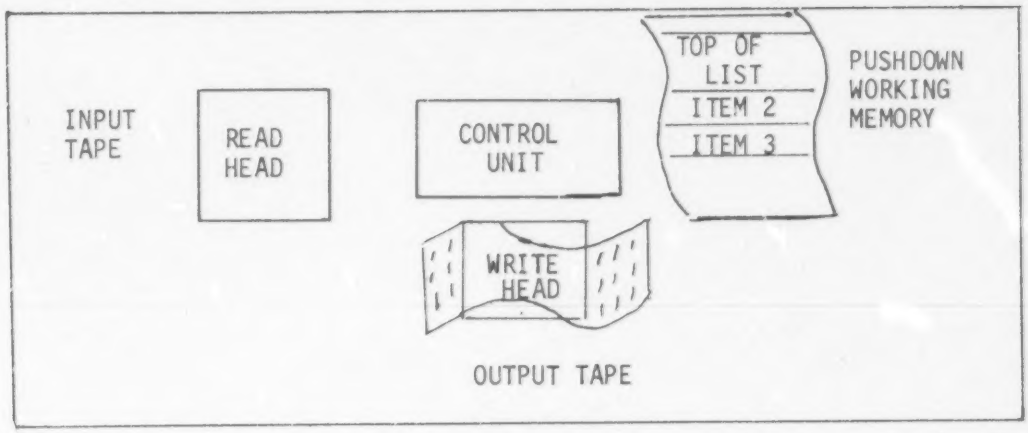


Fig. 18. The Pushdown Automata.

Information Processing Characterization of Automata

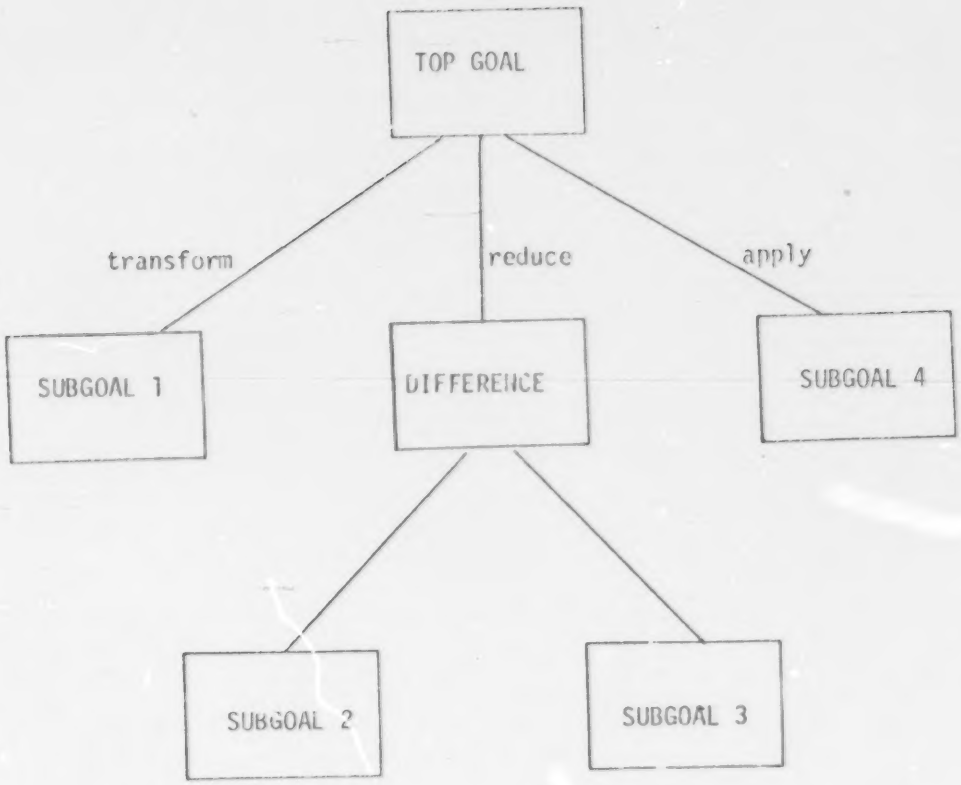
The General Problem Solver (GPS) (Shaw, Simon, Newell & Ellis, 1958) represents a prototype of an information-processing representation of automata. While the model can be considred an automata in the Von Neumann sense of the word, it does not utilize the formal automata theory mathematics. It is discussed here in the context of automata characteristics and the representation problem.

The overall goal for GPS is development of a computer program of human problem-solving that is capable of working with a variety of problems. Generality is the major goal of GPS with the index of generality being the number of solvable problem types. Some of the types of problems successfully handled thus far include sentence parsing, calculus problems, and verbal problems. The kinds of problems attempted are simple by human standards, but they do require intellectual effort of more than a simplistic domain.

The problem-solving techniques of the GSP are based on the concept of purposive behavior, a concept much discussed by Von Neumann as an automata characteristic. The GPS problem-solving techniques are organized by goals. By this, one means that the main function of the proving-solving techniques is to achieve the problem solution or goals. to do this, subgoals are generated in order to reach main goals. A goal is defined in the GPS program as a data structure that provides sufficient information to carry out problem-solving activities, i.e., a goal defines a desired state of affairs, the current situation, and a history of previous attempts to achieve the goal. GPS has four types of goal routines currently, and the necessity for other types of goal routines has not arisen. These four types of goal routines are as follows: (1) Transform Object A into Object B, (2) Reduce difference between Object B and Object A, (3) Apply solution operator to Object A, and (4) Select the elements of set 5 which best fulfill a criterion C.

For each of these goals, methods are generated to obtain the goal. The methods for a given goal are represented via a tree-structured list as shown in Figure 19. This tree is called a "discrimination net" because of contingent-sorting capability. The terminal nodes of the tree are the methods for a goal. The solution selection is performed by discriminating, first at the top node, and then at each node in turn until arriving at a matching node. The learning process in GPS is the growth of these tree structures.

Just as methods for goal routines are represented by trees, the representation of a real object or a concept is also in terms of trees. An object or concept may be any unit in the problem domain which we wish to utilize (i.e., an information unit). The major process of GPS in its attempt to solve problems is tree searching, which is a process of sequentially checking for distinctive feature matches that route an object to its image equivalent. GPS searches for goals, it searches for methods to reach those goals, and it accesses information units by tree searching.



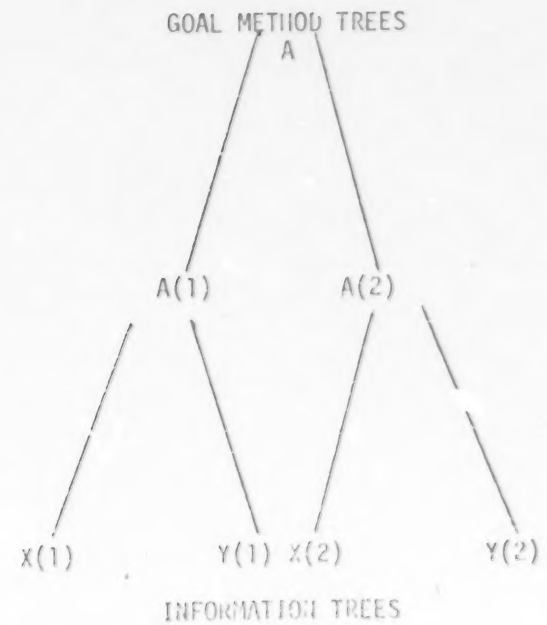


Fig. 19. Examples of Tree Structures in GPS.

GPS uses a general technique called "means-ends analysis" to guide the search through the trees. Means-ends analysis involves subdividing the problem into easier subproblems. It is accomplished by taking differences between what is given and what is desired, *i.e.*, between two objects or between an object and a class of objects, or more concretely, the separating of a mathematical problem into simpler addition or multiplication problems. Thus, it is possible to see that the four subgoal routines mentioned are an integral part of the means-ends analysis and the tree-searching process.

One of the critical questions surrounding GPS and other computer models of problem solvers is the question of memory. Since objects, methods, and goals are all represented by a tree-structured list in GPS, essential memory structure and process are represented by tree structures and processes. The link from one node of a tree to another node is never broken in GPS, *i.e.*, the memory is perfect. For example, all node images can be listed, sorted, or restructured without loss. But human thinking is surprisingly interruptable. These interruptions affect memory in various ways. Input to memory may be disrupted or intermittent in nature (similar to interruptions while reading a novel). Using list structure techniques or stochastic principles (Suppes, 1969), representations of objects in human memory as a tree-structured list can look like a tree with many broken limbs. Thus, GPS offers the potential to represent complex memory processes associated with reading comprehension.

The role of personality processes can also be incorporated with the GPS model (Simon, 1967a or 1967b). Simply, personality processes are conceptualized as interrupt commands that switch the GPS processor to personality subroutines.

Robert Shaw (1968) has suggested an Automaton Model of the human memory system based on the pushdown store. While model is fairly specific to a particular task, it is suggestive of the possible use of automata theory in technical training. Taking into account consistent evidence for performance characteristics which seem to suggest a short- and long-term memory, Shaw proposed a memory system based on two pushdown store transducers illustrated in Figure 20. Each pushdown store represents a functional component of memory. The short-term store (STS) is a pushdown store which accepts inputs from a perceptual system (PS) and places them in its working memory. However, the STS has no control over the working pushdown memory other than the placing of items on the list. It is the long-term store (LTS) which has the transfer control of items between the pushdown list of STS and LTS. It is also the LTS which transfers information back to STS. Only through STS can output be generated to the motor system (MS).

The task this model was to account for is the learning of an aperiodic sequence of symbols. For example, a group of subjects might receive a string of five R symbols followed by five G symbols. The subjects were to anticipate the next symbol and, when a criterion of two blocks (in this example 5 R's and G's make a block) was successively anticipated by the S, and a new block consisting of, for example, seven R's followed by seven G's, was presented to criterion. Several variations on this task were used (including string-ending markers), but they are not discussed here.

Shaw defined 48 rules which characterized the system by predicting output based on the input symbol and the current state of the system (the top of the pushdown store and items below, or the history). In this way he was able to determine which rules Ss used during the task and which ones were not used. Further, the current state of S could always be predicted after the first symbol presentation and knowing the next input could be predicted. Through the various task variations, Shaw found good agreement between the model predictions and the observed data.

Automata Characterization with Stimulus-Responses Paradigms

Suppes (1969) has recently attempted to demonstrate that stimulus-response models of behavior can be expressed as automata. The implications of the theorem have been discussed by Suppes for language learning and the learning of arithmetic algorithms.

The basis for Suppes' theorem is to show, by utilizing principles of conditioning, how a person may be taught with an appropriate reinforcement schedule to respond as an automaton. Suppes points out that one of the major problems initially was to characterize the internal states of the automaton. First attempts centered around identifying states of the automaton with the conditioning state of the organism. This

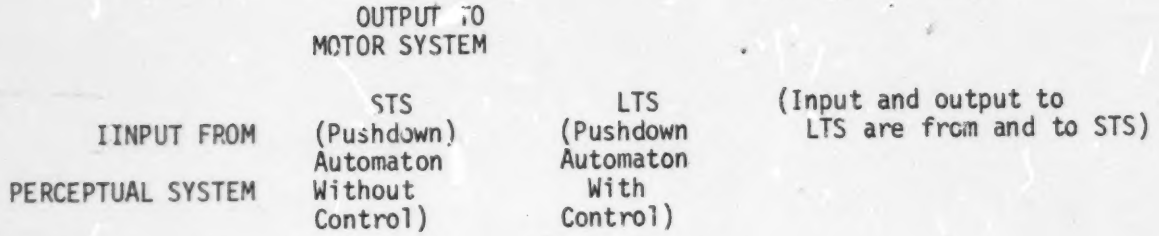


Fig. 20. Automata Memory Model.

approach was abandoned because each conditioning state required a corresponding, different automaton. The correspondence that was finally chosen was to identify the responses of the person with the internal states. Responses can be finitely classed and handled as an automata parameter. In effect, internal states and output are welded into the single component of internal state.

Norman Wexler (1970) has continued the automata work at Stanford in language modeling. Wexler studied learning of the Japanese language based upon an Automaton Model. The specific model used differed from a stock automata requiring no capability to erase memory. Instead, a transducer automata was used which simply generated an output sequence from input and state without relating input to memory. Only one element in memory was required at any given time as opposed to the total memory of a pushdown store. Experiments were run with this model for determining learning sequence of rules.

Offir (1971) has also investigated Automata Models at Stanford as part of a set of models of individual differences in learning and performance. He particularly was interested in the scheduling of blocks and items adaptively. Although not directly applicable, his discussion does present relevant questions about adapting mathematical models in general to individual differences.

Recommendations

The following recommendations are made for automata models in AIS:

- It would be premature at this stage in the development of automata modeling to focus on a particular model with its parameters for an application to AIS. Delay is suggested due to the theoretical and mathematical structure of Automata theory as well as the problem of representation of states and sequence symbols as discussed earlier. Therefore, it is recommended that this class of model be identified as a basic research element in AIS and not become an operational procedure.
- This section has attempted to describe two approaches to representation-information processing and stimulus-response. Although both of these appear promising, they lack sufficient validation to allow a firm prediction concerning their value to AIS. It should, perhaps, be reiterated that what might be gained from these Automata Models is the inclusion of complex human behavior into the adaptive system operations of the AIS. Many models are capable of being used to handle complex behavior at a gross level, but few can even attempt an "in-process" modeling. It is, therefore, recommended that basic research finding in automata be monitored so as to identify any models that may prove useful in AIS during its development.
- Given the conceptual and performance complexities found in the training tasks of the three AIS courses, Automata Models would be potentially appropriate for each of them. Automata Models might be especially useful for the marginal or semiliterate student, since his learning problems and processes could be represented in fine-grained detail and precise remediation applied. It is therefore recommended that Automata Models be investigated for their application for marginal and semiliterate students.

X. SUMMARY AND CONCLUSIONS

Thoughtful assessment of the "state-of-the-art" and current needs of Adaptive Instructional Models reveals the requirement for planning, conceptualizing, and operationalizing efforts, rather than for merely applied engineering efforts. These needs appear to be best met by a multifaceted research and development program. The process of this Research and Development program must parallel the process reflected in the AIM literature search. Accordingly, the first step after this report is prepared is to simulate several of the models described in this document. These simulations will serve to (1) solidify and make operational the concepts and the models, (2) suggest the proper use and ranges of model parameters, and (3) provide the first look at the AIS Adaptive Model data base and its operation. Once AIM's are implemented within the AIS, the models will continue to evolve and change, given evaluative feedback. This evolutionary process must allow for reassessment of current model parameters, the updating of these parameter values, and the introduction of new processes and parameters.

The general conclusions of this report consist of two parts. The first concerns the operational conceptualization of AIM's in Sections II through V, which could be sufficiently defined to be implemented in a real system, namely, AIS. Much of the learning model literature has been concerned with speculative models which have never been implemented and probably never will be. One should recognize that, for the AIS, AIM must not only be implemented, but is the crucial coordinator of the training system.

The second area of findings concerns a mapping of a domain by which varying models described in this report, and those that may develop in the future from new ideas and techniques, could be further integrated, made operational, evaluated, and modified. The operational conceptualization of the adaptive Models for AIS is represented in Figure 21. The models are interrelated in hierarchical fashion according to the nature of the instructional events which follow an adaptive decision. The instructional events (I_j) may be distinguished along either of two dimensions. The first dimension relates to the type of instruction which will be performed. I_1 refers to instruction on a topic, such as power supplies or remedial instruction, *i.e.*, the first level concerns broad, task-determined categories of instruction. I_2 refers to specific instructional lessons such as media presentations or tutorial sequences. I_3 is even more specific, referring to an individual learning "frame" as in Programmed Instruction or CAI.

The second relational dimension focuses on time. In general, as one increases specificity in going from I_1 to I_3, one decreases the time duration of the instructional unit. For discussion purposes, I_1 instruction is generally 30 minutes or more, while I_3 instruction is typically 1 or 2 minutes at most.

For each decision level, an adaptive model has been identified in the figure as it relates to the level of decision to be made within the instructional process. In some cases, an adaptive model will be proposed for more than one decision level. This occurs wherever the nature of the model permits this kind of multiple complexity-time application.

This AIM schema provides the following insights into the actual and the potential model relationships. First, Adaptive Models are inclusive in the sense that drill-and-practice models can be incorporated within a dynamic programming model. Therefore, all the AIM's hierarchically share variables. Secondly, the level of task specification and the training event time will determine the specificity of the decision and monitoring process. Thus, all AIM's will have similar intentions as to their adaptive approaches, but will differ by task time and decision process variables. Finally, the higher a model is in the hierarchy (*e.g.*, Automata Models), the less likely it is that one can operationally utilize it at this time. The best future prediction would be a hierarchical integration of all the models.

The common AIM variables that should be monitored during the evolution of AIS are those described in Section I, since these best summarize the relationships among the Adaptive Models presented here. The five categories of variables that reflect the operational characteristics ar as follows:

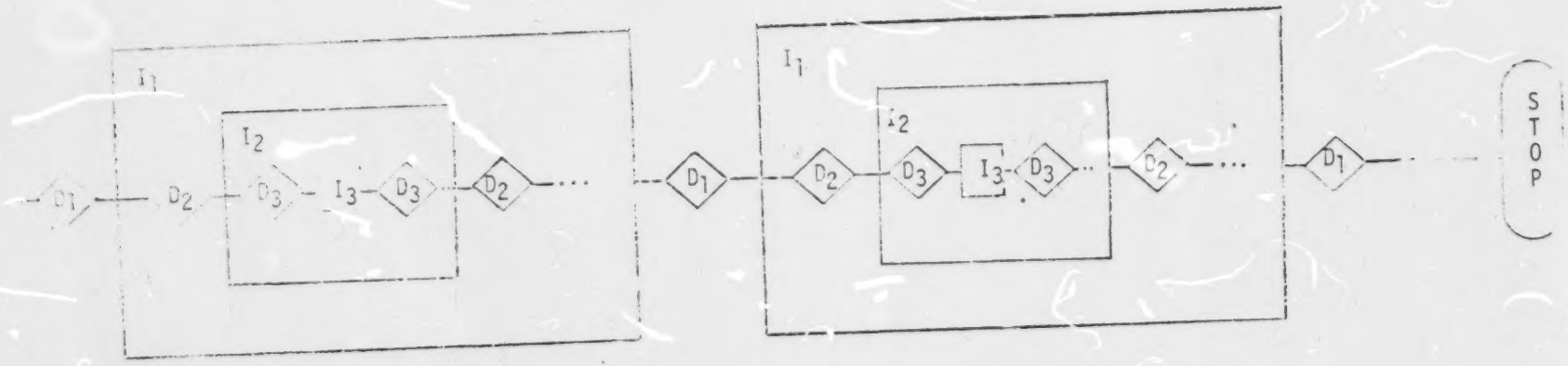
(1) Task characteristics

(2) Instructional mode

(3) Decision processes

(4) Student characteristics and

(5) Instructional resources



D_i - Decision Process of level i

I_j - Instructional event of level j

Potential Instructional Events

I_1 Remedial Instruction
Instruction in Topic X
Consulting Materials

I_2 Textbook
Workbook
Film
Tutorial Sequence
Drill and Practice Sequence
Slide/Tape Presentation

I_3 Drill and Practice Frame
PI Frame

Potential Time Parameters

I_1 30 Minutes or More

I_2 1 Minute to 1 Hour

I_3 Less than 1 Minute

Potential Adaptive Model(s)

D_1 Dynamic Programm
Algorithmic
Regression
Natural Language

D_2 Complex Tutorial
Simple Concept Acquisition
Algorithmic
Regression
Automaton

D_3 Drill and Practi
Complex Tutorial

Fig. 21. Operational Conceptualization of Adaptive Model(s).

In order to reflect these model characteristics through the AIS life cycle, it will be necessary to develop an Adaptive Model's frame of reference for those responsible for the AIS environment. One of the functions of this document has been to map and portray this frame of reference.

Recommendations

In order for AIS and the Adaptive Model component to provide the most cost-effective individualized instruction, the Adaptive Models will require additional conceptualization and validation. The following general tasks are recommended:

- Each of the models described should be simulated to facilitate the specification of initial parameters, roles, and decision rules.
- Each model and its simulation should provide for graduations in number and relational complexity of variables so that minimal, comprehensive, and open-ended models may be devised.
- Each model and the related simulation should allow for variation in parameter values, functional relationships, and observable measures so that the models may be revised according to AIS cost-effectiveness data.
- The Air Force should consider sponsoring a basic research effort, parallel to the AIS effort, into the relationships between student characteristics, instructional parameters, and cost-effectiveness parameters.

Model-specific recommendations are as follows:

- **Drill-and-Practice**
  - The two Drill-and-Practice Models, namely, the performance-contingent pacing model and the task/frame mastery model, should be simulated and implemented within AIS.
  - There are many decision points within a Drill-and-Practice Model. Curently, most of these decisions will need both conceptual and empirical exploration. It is recommended that these variations be incorporated in the AIS research plan.
  - For each review session, a Drill-and-Practice Model should be utilized to formulate the problem list, organize the sequence, and provide optimal allocation of practice per problem type. All instructional decisions should be based on individually determined parameters.
- More specifically for the AIS project, the Drill-and-Practice Model should be utilized in the courses as follows:
  - For Inventory Management, the focus should be on coding/index schemes and classification structures as in security rules;
  - For Precision Measurement Equipment, the major emphasis should be technical and conceptual aspects of the course; and
  - For Weapons Mechanics, the focus should be on conceptual factors of electricity and image/photo requirements of specific weapons.
- **Adaptive Concept Acquisition Model**
  - The proposed Adaptive Concept Acquisition (ACA) Model should be simulated and ultimately field tested since it focuses on a primary requirement of training, namely, concept acquisition. The topics of adaptive prompting, feedback and task/performance-related concepts should be incorporated within the ACA Model or become correlated models.
  - The use of pretask measures (trait measures) should be extended and utilized so as to increase the training efficiencies.

- The most cost-effective use of media and instructional resources should become an operational component within the ACA model approach.
- The ACA model should be extensively employed within each of the three AIS courses and appropriate evaluative comparisons made.

• Adaptive Rule-Learning Model

- The Adaptive Rule-Learning Model should be simulated and ultimately field tested. The related, complex process of problem-solving should also be studied should also be studied and hopefully integrated into Rule-Learning Model.
- Although the adaptive model for rule-learning proposed in this report is based on the current theoretical and research literature, many features of the model are innovative in nature and will require additional research and validation. It is therefore recommended that research be conducted int his area. In addition, the linear regression models and heuristic decision rules utilized by the adaptive model will require further delineation and empirical validation.
- A simulation of the Adaptive Model will facilitate the specification of initial decision rules and regression algorithms. The input variables and instructional decisions should be expanded or revised according to the constraints and characteristics of the simulated adaptive model. It is recommended that two versions of the model be simulated--a full model and a reduced model. The full version of the model would require a highly interactive mode of instruction such as CAI. However, a reduced version of the model could be utilized in a semi-interactive mode such as CMI. Therefore, it is recommended that both versions of the models be simulated. The reduced version would not require an updating of the instructional strategy according to within-task performance data.
- The applicability and extension of the adaptive model for rule-learning into the area of problem-solving should be investigated. However, it is anticipated that instructional models such as Task Teach might prove to be very useful in problem-solving applications in the AIS.
- Provision for research into the role and effects of the number of examples, prompts, types of examples, rule frame structure, and amount and placement of review should be made in the implementation of the adaptive model. This research would provide data for the revision and refinement of the model.

• Algorithmic Regression Model

- An Algorithmic Regression Model should be developed and simulated since it bridges the gap between the description of complex training phenomena and the prescription of effective, individualized instructional events. It is anticipated that, during the early phases of AIS, the Algorithmic Regression Model will be the primary comprehensive prescriptive mechanism.
- Second, the regression approach appears to be especially useful in an interlesson context. Rather than changing or modifying the instructional method *within* and instructional session on the basis of responses, a potentially more effective instructional change can be made by directing the student to another set of materials within the lesson or to a remedial or enhanced lesson.
- Within an operable training system used to capacity, it can be expected that the prescription selected by the regression equation as optimal may be unavailable. A necessary interface to the regression model formulation is a resource allocation model which would provide a list of available resources and estimates of resource use so as to permit optimal resource-spares to be ordered. Thus, not only will more efficient use be made of available resource, but resources can be maintained at an efficient level of supply as well. It is therefore recommended that a resource allocation model be developed as a part of AIS.

- As a final recommendation, validation of the regression models should be carried out over a sufficient period of time by the AIS contractor in order to provide sufficient data to update the beta weights if required. The contractor should also devise a procedure for periodic revalidation and restructuring of the models.

- **Dynamic Programming Model**

  - A study should be made into operational feasibility of the development of a Dynamic Programming Model for AIS. This study should be based upon performance data collected during the initial phases of the AIS program. As the dynamic nature of the individualized training in AIS becomes observable and descriptive in nature, a Dynamic Programming Model should be developed.

  - The development of the dynamic programming model should be phased as follows:

    - Initial system description
    - Single-variable optimization studies
    - Multivariate optimization studies
    - The emerging of cost-effective criteria and decision processes with the evolved dynamic programming model.

  - Each of the AIS course operations could profit from the application of a dynamic programming model. This is especially the case for PME and Weapons Mechanics in that the model would provide for optimal utilization of expensive, high-fidelity simulators and trainers.

- **Natural Language Model**

  - The Natural Language Model described in this report is one of the few in the NLP literature which is educationally oriented and the only NLP model based on a systems approach. The model should be researched further to provide an empirical basis. The funding of such research would not be a long-term investment since the state-of-the-art is sufficient to provide a short-term basis for NLP counseling within AIS.

  - The authoring of NLP dialogues has not been sufficiently recognized as a problem in literature. It is, nevertheless, a problem directly relating to the specification and evaluation of NLP dialogues. The systematic approach of content mapping discussed earlier is an attempt toward solution of this problem. Any educational implementation of NLP or more than a research scale should provide training in this systematic approach.

  - A related problem is the validation of the dialogue system. Several possiblities have been suggested as a result of the work done at Florida State University. The first is to follow a standard systems approach relating instructional objectives to test questions, and, through the hierarchical content map, to categories or levels of the hierarchy. A pretest/posttest procedure would probably suffice for data collection. The second possibility is to use a sorting or categorization task as the testing situation within the same system approach. This would provide needed information concerning memory organization.

  - In respect to the AIS courses, it is recommended that the NLP model be implemented and evaluated, especially in the student evaluation and counseling requirement.

- **Automaton Model**

  - It would be premature at this stage in the development of automata modeling to focus on a particular model with its parameters for an application to AIS. Delay is requested due to theoretical and mathematical structure of Automata theory as well as the problem of representation of states and sequence symbols as discussed earlier. Therefore, it is recommended that this class of model be identified as a basic research elementary AIS and not become an operational procedure.

- This section has attempted to describe two approaches to representation–information processing and stimulus-response. Both of these appear promising, but they lack sufficient validation to allow a firm prediction concerning their value to AIS. It should perhaps be reiterated that what might be gained from these Automata Models is the inclusion of complex human behavior into the adaptive system operations of the AIS. Many models are capable of being used to handle complex behavior at a gross level, but few can even attempt an "in-process" modeling. It is, therefore, recommended that basic research findings in automata be monitored for the purpose of identifying any models that would prove useful in AIS during its development.

- Given the conceptual and performance complexities found in the training tasks of the three AIS courses, Automata Models would be potentially appropriate for each of them. Automata Models might be especially useful for the marginal or semiliterate student, since his learning problems and processes could be represented in fine-grained detail and precise remediation applied. It is therefore recommended tha Automata Models be investigated for their application to marginal and semiliterate students.

GLOSSARY OF TERMS

Academic Counseling–The process of providing factual information and guidance to students concerning progress through courses, potential additional courses, and career fields.

Adaptive Instructional Model–One of many multifaceted decision structures which use student characteristics, instructional mode parameters, and resource load characteristics in order to assign students to appropriate instructional conditions and media.

Adjustment Counseling–The process of providing the student with help and guidance concerning his own personal problems as may be related to his academic and other endeavors.

Air Force Specialty–A grouping of positions which require common qualifications.

Air Force Specialty Code–A combination of meaningful digits used to identify an Air Force Specialty.

Audiovisual Media–Media utilizing the senses of hearing and sight to encourage or carry on the learning process.

Behavioral Objectives–The specification of the goals of instruction such that each statement contains an identification of terminal behavior, the minimal Standards for acceptable performance, and the conditions under which they are to be performed.

Career Guidance–The process of providing the student with information concerning his career, both within and out of the Air Force.

Cognitive Activities–Those activities associated with the learning of specific facts. procedures, decision skills. (see Learning Activities).

Computer-Assisted Instruction–A training methods involving man machine interactions utilizing a computer to present information to students. The computer interaction can involve multimedia presentations, question-answering, testing, and/or inquiry.

Computerized Measurement System–A system of evaluating student performance through adaptive-testing strategies based primarily on sequence.

Computer-Managed Instruction–A method of teaching that utilizes a computer for diagnostic assessment, CAI, simulation, counseling, resource allocation, and record keeping.

Cost-Effectiveness–A Measure of the relative effectiveness of a system as related to the cost of the system. Effectiveness may be operationally defined within AIS as the continuous operation of the hardware components, smooth operation of software development, and 90 percent or more students completing AIS courses within 80 percent of current instructional time. Cost is operationally defined in terms of both fiscal and time parameters.

Criterion Objective–An objective requiring a terminal action or an end product of the student at the completion of a unit or lesson.

Criterion Test–A test designed to measure student attainment of criterion objectives.

Curriculum–A specific course(s) of study relating to a particular job specialty. Curriculum is the all-encompassing term for the instructional system software, which includes management and training materials, as well as media and instructional strategies.

Discussion Method–A method of instruction in which the instructor uses questions to cause students to participate actively in a learning situation by exchanging ideas, opinions, and experiences to reach conclusions that will support learning objectives.

Drill-and-Practice–An instructional technique in which words, problems, and pictures, are placed before the student for his definition, identification, and solution, and which are repeated a number of times, the number of times determined by the performance of the student.

Dynamically Generated–Any instructional material or test item sequence which is supplied online to the student or instructor and which is selected or constructed as a response to input of the student or instructor.

Educational Technology–The application of principles of modern behavioral science and technology to education.

Enabling Objective–The identification of a knowledge or skill that must be learned to permit satisfactory achievement of a criterion objective.

Entering Behavior–The student's level of knowledge or skill before instruction begins. It refers to his prior learning, motivational states, intellectual ability and development, and cultural and social determinants of his learning ability.

Evaluation Plan–A schedule of the activities and/or projects planned to determine the effectiveness of a course or group of courses in producing graduates qualified to perform job requirements.

Feedback to Student–Information provided to the student regarding the correctness of his response and the quality of his performance.

Feedback to System–Information obtained from student responses which may be used to make adaptive instructional decisions or to revise the instructional program.

Formative Evaluation–That evaluation based on student response data which takes place during materials development in order to aid in the revision of the materials to increase their effectiveness (see Summative Evaluation).

Frame–A segment of material which the student handles at one time. It may vary from a few words to a full page (or CRT screen) or more. In almost all programming methods, it will require at least one response (overt or covert) and provide for knowledge of results before the student proceeds to the next frame.

Games–This instructional technique involves role playing and decision-making activities in order to develop cognitive and affective skills in an often informal manner. Games differ from a similar technique, simulation, in that rules are utilized to guide the progress of the student through the game situation and the correspondence with "real" phenomena is often greater in the game (see Simulation).

Hands-on Experience–Student practice on actual equipment, simulators, or training aids.

Hierarchical Analysis–A method of task analysis in which the terminal behavior is separated into a number of prerequisite capabilities, forming a hierarchy.

Instructional Sequence Decisions–Those decisions having to do with the determination of the order or succession of instructional units.

Instructional Strategies–The series of decision structures which determine the dynamic nature of instruction. The strategies may include such as combinations of media selection, pacing, difficulty level, and readability level.

Instructional System–An integrated combination of resources (students, instructors, materials, equipment, and facilities), techniques and procedures required to assist the student in achieving specified learning objectives.

Instructors–Those personnel who, by training in the specialty field and in the instructor training course, are qualified to teach ATC Technical Training courses (see Monitors).

Interactive Testing Mode–That mode of testing which will typically take place at an interactive computer terminal. Testing in this mode will often involve a sequential testing activity in which succeeding test items given to the student are functions of the student's responses to previous test items.

Learner Strategies–Those algorithms and decision structures which are employed by students for the purpose of managing their own instruction, *e.g.*, pacing, media selections, content decisions, difficulty and redundancy levels.

Mastery–An optimal degree to which content or skills are learned. This may be absolute–100 percent accuracy, or relative–A specified minimum accuracy in a specified number of trials.

Module–An entire instructional unit developed via a systems approach which includes a specification of enabling and criterion objectives, content presentation, and evaluation processes.

Monitors–The class of instructional personnel which are not qualified as instructors but who keep track of necessary inclass training materials, and media, and who supervise students in the absence of a trained instructor. Monitors may be considered "teachers' aides" (see Instructors).

Motor Skills–Those skills requiring manual dexterity, *e.g.*, movement involving fingers, arms, and legs.

Multimedia–Use of more than one medium to convey the content of instruction. Media available for use may include, but need not be limited to texts, programmed instruction, audio and video tapes, slides, films, film loops, television, and computers.

Natural Language Processing–The capability of CAI to interpret student input of natural English and respond accordingly, also in natural English.

Off-line–That part of a computer system which is not under the control of the central processor.

On-line–That part of a computer system which is under the direct control of the central processor.

Performance Activities–Those activities specifically related to performance on actual equipment such as laboratory work and supervised motor activities.

Predicted Pacing Paradigm–The set of decision rules which are a part of the Adaptive Instructional Model and which serve to determine optimal pacing requirements on an individualized basis.

Response Analysis–The analysis of a student's response in terms of its correctness or incorrectness, latency, or other factors as may be appropriate for the response or for the instructional researcher.

Response Collection–The recording and storing of student responses to instructional materials.

Sequencing–The process by which learning experiences are ordered to provide effective and efficient learning.

Sequential Testing–An adaptive testing strategy in which the type and number of test items presented to each student are variable and are based on the student's response to immediately preceding items.

Simulation–A technique in which "real-world" phenomena are mimicked, in an often low-fidelity situation, in which costs may be reduced, potential dangers eliminated, and time compressed. The simulation may focus on a small subset of the features of the actual real-world situation. Simulation differs from another technique, gaming, in that rules and role playing typically do not take place (see Games).

Simulator–Any machine or apparatus that simulates a desired condition or set of conditions.

Student Coping Behaviors–Those strategies or activities which students use in meeting or solving a particular problem situation.

Student Critique–Student feedback to course developers and administrators concerning a given unit or block of instruction. It should provide for a critical systematic evaluation of all phases of the instruction including content, presentation, and instruments.

Summative Evaluation–That evaluation of instructional training materials which takes place in the actual classroom environment and which is designed to provide data for effectiveness analyses. This type of evaluation takes place following the major development of the material (see Formative Evaluation and Ongoing Evaluation).

Systems Approach to Instruction–The series of procedures which is employed by educational psychologists, instructional technolgists, and curriculum developers to design and evaluate instructional programs.

Task–A unit of work activity which forms a significant part of a work assignment done by an individual.

Task Analysis–The process of breadking down a particular skill into its subordinate tasks and subskills. The task analysis serves as a method for the definition and interrelationship of skills necessary in the Air Force job categories.

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